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Co-Adaptation in Upper-Limb Prosthetics: Interactive Machine Learning applied to Myocontrol

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Abstract

For many years, myoelectric prostheses — upper-limb prosthetic devices controlled by one's own muscle signals — have been much-heralded innovations for people with limb absence. Developments are manifold and have promised mind-controlled, easy-to-use devices for everyone. However, only a fraction of what was promised has been delivered. To this day, users have issues with stability in various situations, difficulty in naturally and reliably controlling their prosthesis and frustration with an extensive learning process for said control.

Interaction is key to resolving the issues of myoelectric prostheses, and involving people who need such devices is thus essential. Therefore, we have investigated the **co-adaptation** of the user and prosthesis through **incrementality** in myocontrol to advance the field of upper-limb prosthetics. Our contribution to the field covers three distinct areas. These are the detection and interpretation of **muscle signals**, theoretical considerations regarding **interaction** and novel concepts in the **assessment** of modern myoelectric prostheses.

Besides Electromyography (EMG), further methods such as Forcemyography (FMG) are valid muscle signal detection techniques. We have shown the merits of using FMG in myocontrol in an online user study, where EMG and FMG were fused. We have also found that action interference is lower for FMG compared to EMG, leading to higher control stability. Furthermore, we have designed a transparent myocontrol algorithm and investigated it in a user study. By reducing the complexity of the controller, we were able to show the capability of the user to abstract to untrained tasks.

In order to approach interaction in a structured manner, we took the view of Radical Constructivism (RC) on prosthesis and user. Through the rich theoretical background of RC in the area of learning, we were able to show that interaction indeed is an improvement for prosthetic control, and the change of perspective might offer further benefits.

Finally, we developed a novel assessment protocol for multi-articulated upper-limb prostheses, the Simultaneous Assessment and Training of Myoelectric Control (SATMC) protocol. It considers important aspects of modern prosthetic devices, such as the learning process, the usage of different actions in different situations and the possibility of interaction. We performed a longitudinal user study according to the SATMC protocol and were able to show an effective learning process of a myocontroller based on incremental machine learning with a high level of satisfaction for the user.

In summary, we implemented interactive co-adaptation at different stages of prosthetic control, starting at the sensor level all the way to a comprehensive long-term evaluation of a person with limb absence in activities of daily living. The integration of these findings in modern upper-limb prostheses will, in our opinion, lead to substantial improvements for people with limb absence.

Zusammenfassung

Myoelektrische Prothesen — Prothesen der oberen Gliedmaßen gesteuert durch Muskelsignale — werden seit Jahren als herausragende Innovation für Betroffene angepriesen, die gedankengesteuerte, einfach zu bedienende Geräte verspricht. Jedoch erfahren Anwender*innen noch immer Probleme im Bereich der Stabilität, Schwierigkeiten bei der intuitiven und zuverlässigen Steuerung, sowie Frustration bezüglich des langwierigen Lernprozesses für ebendiese Steuerung.

Im Zentrum der Lösung der genannten Herausforderungen liegt die Einbeziehung Betroffener in die Weiterentwicklungen. Die vorliegende Forschungsarbeit hat sich daher mit der **Koadaption** von Anwender*innen und Prothese durch **Inkrementalität** der Myokontrolle auseinandergesetzt. Im Wesentlichen umfassen die Beiträge die drei Aspekte: Erfassung und Interpretation von **Muskelsignalen**, theoretische Überlegungen zur **Interaktion**, sowie neuartige Konzepte zur **Bewertung** moderner myoelektrischer Prothesen.

Neben Elektromyographie (EMG) lassen sich Muskelsignale über weitere Methoden, wie z.B. die Kraftmyographie (FMG), erfassen. Eine Nutzer*innenstudie, in der EMG und FMG miteinander fusioniert wurden, konnte belegen, dass die gegenseitige Interferenz der Aktionen bei FMG geringer ausfällt als bei EMG, was eine höhere Stabilität der Steuerung ermöglicht. Weiterhin wurde im Rahmen der Forschungsarbeit ein transparenter Algorithmus zur Myokontrolle entwickelt und in einer Nutzer*innenstudie untersucht. In dieser Studie konnte demonstriert werden, dass die Reduktion der Komplexität der Steuerung die Fähigkeit der Anwender*innen zur Abstraktion nicht-trainierter Aufgaben entscheidend verbessert.

Zur Strukturierung der Interaktion wurde das theoretische Konzept des Radikalen Konstruktivismus (RC) angewandt. Aufgrund des umfangreichen theoretischen Hintergrundes des RC im Bereich des Lernens konnte entsprechend dargestellt werden, dass und inwieweit die Nutzer*innen-Interaktion zu einer Verbesserung der Prothesensteuerung führt.

Letztlich wurde unter Berücksichtigung verschiedener Aspekte neuartiger Prothesen — wie z.B. dem Lernprozess, die Anwendung verschiedener Aktionen in unterschiedlichen Situationen, sowie die Möglichkeit der Interaktion — ein neuartiges Bewertungsprotokoll entwickelt. Basierend auf dem SATMC-Protokoll (Simultaneous Assessment and Training of Myoelectric Control) wurde eine Langzeitstudie durchgeführt, im Rahmen derer ein effektiver Lernprozess eines auf inkrementellem maschinellem Lernen basierenden Myocontrollers mit hoher Nutzer*innenzufriedenheit nachgewiesen werden konnte.

Zusammenfassend wurde also eine interaktive Koadaption auf unterschiedlichen Ebenen der Prothesensteuerung implementiert, von der künftige Generationen von Prothesen der oberen Gliedmaßen profitieren werden.

Acknowledgement

to Hupsi
to my family
to my friends

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Publication Preface

The contribution of this dissertation is based on the following four first-author publications:

Publication 1

Markus Nowak, Thomas Eiband, Eduardo Ruiz Ramírez, and Claudio Castellini, "Action Interference in Simultaneous and Proportional Myocontrol: Comparing Force- and Electromyography". In: *Journal of Neural Engineering* 17.2 (Mar. 2020), 026011. DOI: 10.1088/1741-2552/ab7b1e

Publication 2

Markus Nowak, Ivan Vujaklija, Agnes Sturma, Claudio Castellini, and Dario Farina, "Simultaneous and Proportional Real-Time Myocontrol of Up to Three Degrees of Freedom of the Wrist and Hand". In: *IEEE Transactions on Biomedical Engineering* 70.2 (Feb. 2023), pp. 459–469. DOI: 10.1109/TBME.2022.3194104

Publication 3

Markus Nowak, Claudio Castellini, and Carlo Massironi, "Applying Radical Constructivism to Machine Learning: A Pilot Study in Assistive Robotics" In: *Constructivist Foundations* 13.2 (2018), pp. 250–262. constructivist.info/13/2/250

Publication 4

Markus Nowak, Raoul M. Bongers, Corry K. van der Sluis, Alin Albu-Schäffer, and Claudio Castellini, "Simultaneous Assessment and Training of an Upper-Limb Amputee using Incremental Machine-Learning-based Myocontrol: A Single-Case Experimental Design". In: *Journal of NeuroEngineering and Rehabilitation* 20.1 (Apr. 2023), 39. DOI: 10.1186/s12984-023-01171-2

Further Publications

Furthermore, we were able to author and contribute to a number of publications. With the exception of one publication [f], all of these publications thematically deal with the same topic as this thesis. Some of these publications are preliminary work leading up to the core publications mentioned above, and some build on their findings.

[a] Castellini, C., Hertkorn, K., Sagardia, M., Sierra González, D., **Nowak, M.,** "A Virtual Piano-Playing Environment for Rehabilitation Based upon Ultrasound Imaging". In: *5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*. Aug. 2014, pp. 548–554. DOI: `10.1109/BIOROB.2014.6913835`.

[b] Castellini, C., **Nowak, M.,** "Emg-Based Prediction of Multi-Dof Activations Using Single-Dof Training: A Preliminary Result". In: *Myoelectric Controls / Powered Prosthetics Symposium (MEC)*. 2014, pp. 42–46.

[c] Gijsberts, A., Bohra, R., Sierra González, D., Werner, A., **Nowak, M.**, Caputo, B., Roa, M. A., Castellini, C., "Stable Myoelectric Control of a Hand Prosthesis Using Non-Linear Incremental Learning". In: *Frontiers in Neurorobotics* 8 (2014). DOI: `10.3389/fnbot.2014.00008`.

[d] **Nowak, M.** "Simultaneous and Proportional Control of Hand Prostheses with Multiple Degrees of Freedom: A New Method of Improving the Training Process". Monograph. Technische Universität München, 2014.

[e] Brunelli, D., Tadesse, A. M., Vodermayer, B., **Nowak, M.**, Castellini, C., "Low-Cost Wearable Multichannel Surface EMG Acquisition for Prosthetic Hand Control". In: *2015 6th International Workshop on Advances in Sensors and Interfaces (IWASI)*. June 2015, pp. 94–99. DOI: `10.1109/IWASI.2015.7184964`.

[f] Comerford, A., Chooi, K. Y., **Nowak, M.**, Weinberg, P. D., Sherwin, S. J., "A Combined Numerical and Experimental Framework for Determining Permeability Properties of the Arterial Media". In: *Biomechanics and Modeling in Mechanobiology* 14.2 (Apr. 2015), pp. 297–313. DOI: `10.1007/s10237-014-0604-6`.

[g] **Nowak, M.**, Castellini, C., "Wrist and Grasp Myocontrol: Simplifying the Training Phase". In: *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*. Aug. 2015, pp. 339–344. DOI: `10.1109/ICORR.2015.7281222`.

[h] Castellini, C., Bongers, R. M., **Nowak, M.**, van der Sluis, C. K., "Upper-Limb Prosthetic Myocontrol: Two Recommendations". In: *Frontiers in Neuroscience* 9 (2016). DOI: `10.3389/fnins.2015.00496`.

[i] **Nowak, M.**, Aretz, B., Castellini, C., "Wrist and Grasp Myocontrol: Online Validation in a Goal-Reaching Task". In: *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. Aug. 2016, pp. 132–137. DOI: `10.1109/ROMAN.2016.7745101`.

[j] **Nowak, M.**, Castellini, C., "The LET Procedure for Prosthetic Myocontrol: Towards Multi-DOF Control Using Single-DOF Activations". In: *PLOS ONE* 11.9 (Sept. 2016), e0161678. DOI: 10.1371/journal.pone.0161678.

[k] Kossyk, I., **Nowak, M.**, Nissler, C., Castellini, C., Márton, Z.-C., "Virtual Reality-System Und Verfahren Zum Betreiben Eines Solchen". DE102016205849A1. Oct. 2017.

[l] Nissler, C., Connan, M., **Nowak, M.**, Castellini, C., "Online Tactile Myography for Simultaneous and Proportional Hand and Wrist Myocontrol". In: *Myoelectric Control and Upper Limb Prosthetics Symposium (MEC)*. 2017, p. 94.

[m] **Nowak, M.**, Bongers, R. M., van der Sluis, C. K., Castellini, C., "Introducing a Novel Training and Assessment Protocol for Pattern Matching in Myocontrol: Case-Study of a Trans-Radial Amputee". In: *Myoelectric Control and Upper Limb Prosthetics Symposium (MEC)*. 2017, p. 78.

[n] **Nowak, M.**, Eiband, T., Castellini, C., "Multi-Modal Myocontrol: Testing Combined Force- and Electromyography". In: *2017 International Conference on Rehabilitation Robotics (ICORR)*. July 2017, pp. 1364–1368. DOI: 10.1109/ICORR.2017.8009438.

[o] **Nowak, M.**, Engel, S., Castellini, C., "A Preliminary Study Towards Automatic Detection of Failures in Myocontrol". In: *Myoelectric Control and Upper Limb Prosthetics Symposium (MEC)*. 2017, p. 82.

[p] Patel, G. K., **Nowak, M.**, Castellini, C., "Exploiting Knowledge Composition to Improve Real-Life Hand Prosthetic Control". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 25.7 (July 2017), pp. 967–975. DOI: 10.1109/TNSRE.2017.2676467.

[q] Strazzulla, I., **Nowak, M.**, Controzzi, M., Cipriani, C., Castellini, C., "Online Bimanual Manipulation Using Surface Electromyography and Incremental Learning". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 25.3 (Mar. 2017), pp. 227–234. DOI: 10.1109/TNSRE.2016.2554884.

[r] Meattini, R., **Nowak, M.**, Melchiorri, C., Castellini, C., "Towards Improving Myocontrol of Prosthetic Hands: A Study on Automated Instability Detection". In: *2018 IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids)*. Nov. 2018, pp. 1–7. DOI: 10.1109/HUMANOIDS.2018.8625021.

[s] Bongers, R. M., Franzke, A. W., Kristoffersen, M. B., Valka, T. A., **Nowak, M.**, van der Sluis, C. K., Castellini, C., "Implications of Movement Coordination for Developing Myocontrolled Prostheses". In: *TIPS-Trent International Prosthetics Symposium*. 2019, pp. 30–30.

[t] Heiwolt, K., Zito, C., **Nowak, M.**, Castellini, C., Stolkin, R., "Automatic Detection of Myocontrol Failures Based upon Situational Context Information". In: *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*. June 2019, pp. 398–404. DOI: 10.1109/ICORR.2019.8779478.

[u] Meattini, R., **Nowak, M.**, Melchiorri, C., Castellini, C., "Automated Instability Detection for Interactive Myocontrol of Prosthetic Hands". In: *Frontiers in Neurorobotics* 13 (2019). DOI: 10.3389/fnbot.2019.00068.

[v] Nissler, C., **Nowak, M.**, Connan, M., Büttner, S., Vogel, J., Kossyk, I., Márton, Z.-C., Castellini, C., "VITA—an Everyday Virtual Reality Setup for Prosthetics and Upper-Limb Rehabilitation". In: *Journal of Neural Engineering* 16.2 (Mar. 2019), p. 026039. DOI: 10.1088/1741-2552/aaf35f.

[w] **Nowak, M.**, Nissler, C., Weber, B. M., Schäfer, M., Castellini, C., "VVITA–Validation of the Virtual Therapy Arm". In: *TIPS-Trent International Prosthetics Symposium.* 2019, pp. 30–30.

[x] **Nowak, M.**, Vujaklija, I., Castellini, C., Farina, D., "Highly Intuitive 3-DOF Simultaneous and Proportional Myocontrol of Wrist and Hand". In: *Converging Clinical and Engineering Research on Neurorehabilitation IV*. Biosystems & Biorobotics. Cham: Springer International Publishing, 2020, pp. 377–382. DOI: 10.1007/978-3-030-70316-5_60.

[y] Sziburis, T., **Nowak, M.**, Brunelli, D., "Prototype Reduction on sEMG Data for Instance-Based Gesture Learning towards Real-Time Prosthetic Control". In: *Proceedings of the 14th International Joint Conference on Biomedical Engineering Systems and Technologies - BIOSIGNALS*. INSTICC. SciTePress, 2021, pp. 299–305. DOI: 10.5220/0010327500002865.

[z] Sziburis, T., **Nowak, M.**, Brunelli, D., "KNN Learning Techniques for Proportional Myocontrol in Prosthetics". In: *Converging Clinical and Engineering Research on Neurorehabilitation IV*. Biosystems & Biorobotics. Cham: Springer International Publishing, 2022, pp. 679–683. DOI: 10.1007/978-3-030-70316-5_109.

Contents

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Acronyms

ACMC	Assessment of Capacity for Myoelectric Control
ADL	Activity of Daily Living
ANN	Artificial Neural Network
ARM	Arm Prosthesis Race
BBT	Box and Blocks Test
CRT	Clothespin Relocation Task
DOF	Degree of Freedom
ECG	Electrocardiography
EIT	Electrical Impedance Tomography
EMG	Electromyography
FMG	Forcemyography
GMM	Gaussian Mixture Model
HD-sEMG	High-Density Surface Electromyography
HMM	Hidden Markov Model
iML	incremental Machine Learning
IMU	Inertial Measurement Unit
iRRRFF	incremental Ridge Regression with Random Fourier Features
KRR	Kernel Ridge Regression
LDA	Linear Discriminant Analysis
LET	Linearly Enhanced Training
LR	Linear Regression
MAV	Mean Absolute Value
ML	Machine Learning
MLP	Multi-Layer Perceptron

MMG	Mechanomyography
MU	Motor Unit
MUAP	Motor Unit Action Potential
MVC	Maximum Voluntary Contraction
NMF	Non-negative Matrix Factorisation
NMJ	Neuromuscular Junction
OV	Overshoots
PE	Path Efficiency
PLP	Phantom Limb Pain
PWD	Probability-Weighted Regression
RBF	Radial Basis Functions
RC	Radical Constructivism
RMS	Root Mean Square
RMSE	Root-Mean-Square Error
RR	Ridge Regression
SATMC	Simultaneous Assessment and Training of Myoelectric Control
SCED	Single Case Experimental Design
sEMG	Surface Electromyography
SHAP	Southampton Hand Assessment Procedure
SMG	Sonomyography
SP	Speed
SPC	Simultaneous and Proportional Control
SR	Success Rate
SVM	Support Vector Machine
SVR	Support Vector Regression
TAC	Target Achievement Control
TCT	Task Completion Time
TD	Time Domain
TFD	Time-Frequency Domain
TMG	Tactile Myography
TMR	Targeted Muscle Reinnervation
TP	Throughput
TSD	Time-Serial Domain
TSR	Targeted Sensory Reinnervation
VITA	Virtual Therapy Arm
VR	Virtual Reality

1 Introduction

The human-made world is built for interaction with hands. We grasp tools with our hands, we open doors by turning the door handles with our hands, and we use computers with our hands. A partial or full loss or congenital absence of one's hands or arms severely influences the ease of interacting with the world. Beyond physical interaction, we also communicate with our limbs and express ourselves through them. Having that in mind, the absence of a limb has social implications affecting participation in social activities [1].

Manifold options exist to support people with limb absence in regaining some functionality and autonomy. Although developments in prosthetics in recent decades have been substantial, a number of challenges still prevent their success as a satisfactory replacement.

1.1 Prosthetics

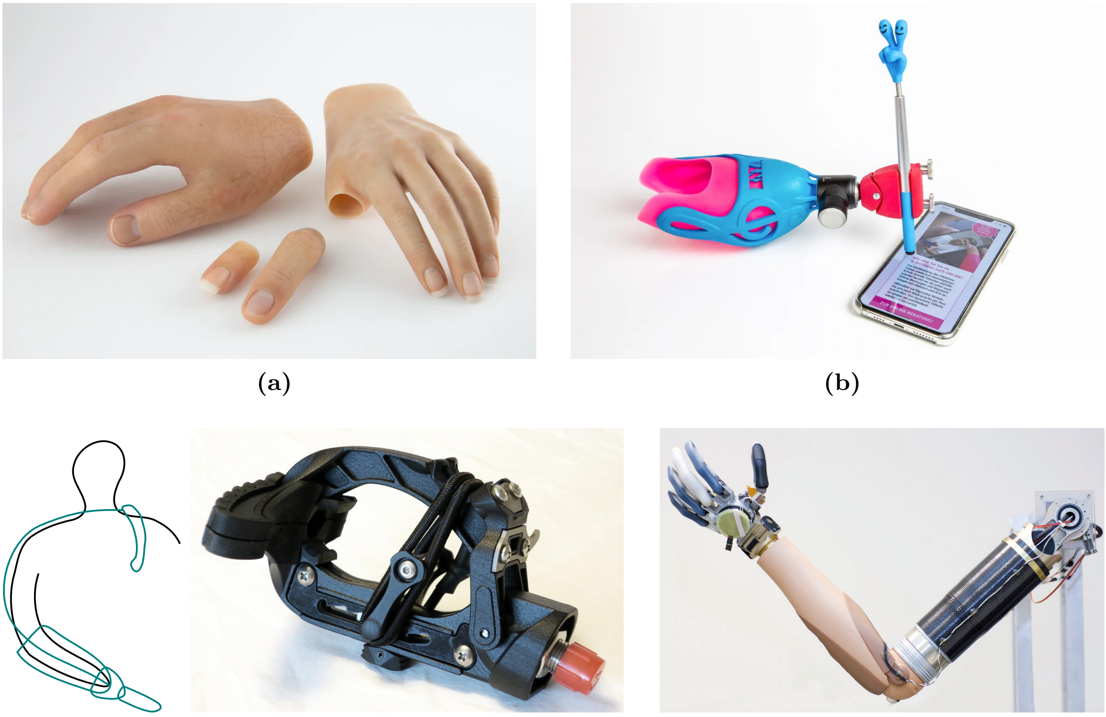
Prosthetic devices are options to reenable people with limb absence to interact with their environment. These can be categorised coarsely in **active** and **passive** prostheses, and a few examples can be found in Figure 1.1.

Among passive prostheses, there are options that aim to resemble the absent limb purely from a **cosmetic** point of view. Figure 1.1a depicts some examples that bear a high resemblance to hands and fingers.

Beyond cosmetics, prostheses can also be tailored for individual tasks. For example, these can be prostheses for swimming that are shaped like a fin rather than a hand or for cycling that provide a connector to the handlebar of a bicycle. These follow rather the concept of a tool and provide the maximum functionality in these situations. An example of a prosthesis with a contraption to hold a pen can be seen in Figure 1.1b. These **functional** prostheses also fall in the category of passive prostheses, which require external manipulation to change their configuration [2].

There are also options that are active and provide functionality to the wearer based on the capabilities of human hands. Examples are hooks that can be controlled using one's body and provide substantial functionality compared to their level of complexity, see Figure 1.1c. Controlling these **body-powered** prostheses only requires mechanical cables and no added electronic components. This bears two advantages. First, low technical complexity makes these devices rather robust. Second, due to the cable-driven control with another body part, body-powered prostheses inherently provide haptic feedback to the wearer [3].

However, the prosthesis type that provides the highest potential to be an equivalent human hand or arm replacement in any given situation is a mechanical **self-powered** prosthesis. Modern mechanical hands have individual finger actuation and can include wrist modules with multiple Degrees of Freedom (DOFs) and arms with actuated elbow and shoulder joints, e.g. the *Modular Prosthetic Limb* [4], see Figure 1.1d. This prosthesis type offers the most functionality to the wearer and, due to its number of controllable DOFs, is often referred to as a **multi-articulated prosthesis**. To fully harness the level of functionality, the wearer needs to control the prosthetic device reliably. As the functionality of modern prosthetic devices increases, so does the complexity of controlling them. It might require a considerable effort of the wearer to master such a device.



(a) **(b)** **(c)** **(d)**

Figure 1.1: Different prosthesis types: (a) cosmetic [5]; (b) functional or everyday aid [5]; (c) body-powered hook (sketch based on [6]; modern hook [7]); (d) self-powered prosthetic arm [4]

Each of these prostheses is a unique solution, which offers benefits for some wearers but not necessarily for others. The choice of prosthesis type is individual [8]. No prosthesis has yet reached a level of proficiency to be a universal solution for everyone.

1.2 Myoelectric Prostheses

This thesis will focus on modern multi-articulated prosthetic devices. Although this prosthesis type could offer the highest benefits, rejection rates of around 44% have been reported in the past [9]. Numerous aspects for improvement were identified. These are most often concerned with the control of the prosthesis [1, 10], which is based on muscle signals. This type of control is called **myocontrol** and originates from the Greek word for muscle $\mu\upsilon\varsigma$/*mys*. For the scope of this thesis, we will briefly introduce myocontrol in this section in order to aptly describe the challenges that come with this type of control. Section 2.3 will cover the topic in more detail.

Skeletal muscles move our body by actuating limbs and joints. After an amputation, a portion of the skeletal muscles of the amputated limb remains. The situation is similar for the congenital absence of a limb. In both cases, muscle structure is present that does not serve the purpose of moving a part of a limb. However, these muscles remain innervated and can be actuated voluntarily. Muscular activity can be measured, and the most common method for this purpose is Electromyography (EMG). It detects muscular activity based on the electric field that is created in the muscle-contraction process.

There are two different ways of utilising the EMG signal for prosthetic control. The first one, known as **direct control**, uses the signals directly to control a DOF of a prosthesis. Usually, two sensors are placed on opposing sides of the forearm; one side is associated with opening and the other one with closing the hand. A threshold on the signal magnitude determines when an action is triggered. In case the prosthesis supports a number of different actions, these can be cycled through by a specific muscle activation, e.g. simultaneous signals at both sensors. The second method involves Machine Learning (ML). Instead of using the EMG signals directly, an **ML-based** layer first interprets the signals and then uses the detected actions as control inputs for the prosthesis. Usually, this method involves training or calibration by the wearer, during which EMG signals are collected and associated with certain actions of the prosthesis.

ML-based control approaches can be used to operate multi-articulated prostheses. Only two systems of that kind have made it to the market so far: the Ottobock Myo Plus [11] and the Coapt Complete Control [12]. Although advanced, a number of challenges still remain in their usage. Their improvement is the focus of this thesis.

1.3 Problem Statement

Prosthetic arm technology is still so limited
that I become more disabled when I wear one.

Britt H. Young [13]

Although an extreme statement, the quote by Britt H. Young, a writer, geographer and person with limb absence, summarises the dissatisfaction with meeting the promises of modern prostheses quite well. On a more specific level, a number of current challenges have been identified.

A common source of dissatisfaction is the robustness of the control. This has been reported in a number of studies [1, 10, 14, 15]. People with limb absence voiced the wish for “lower reaction and execution times”, a higher level of intuitiveness or “to allow the execution of the daily life tasks”.

A recent review [16] groups the current challenges in myocontrol into four categories:

Limb position effect: Scheme et al. [17] have first described the influence of this effect on intent detection. Relative movement between muscles and skin is possible. Therefore, changing the pose of one's limb can lead to a displacement between the two. Measuring the EMG signal on the surface of the skin, hence, can lead to measurements of another part of a muscle or an entirely different muscle. Additionally, depending on the limb position, a varying amount of muscular activity is required to counteract the gravitational force, thus changing the EMG signal as well. These changes can negatively influence the detection of the user's intent.

Contraction intensity effect: This effect is similar to the limb position effect but covers the negative effects that result from changes in the EMG signal based on different levels of muscle contraction intensity. The increase in muscular activity is based on specific recruitment principles. These principles affect the frequency properties at different levels of muscular activity and can make the relationship between muscular activity and EMG amplitude non-linear [18].

Electrode shift effect: Relative changes between skin and electrode can have negative influences on signal interpretation. A shift can result in measuring a different muscle or a muscle area with lower signal quality. Furthermore, the lift-off of an electrode leads to signal loss and can introduce noise into the system. A provision with a well-fitted prosthetic socket can reduce this issue considerably. For the purpose of this thesis, we will not consider this an issue of ML-based myocontrol but rather of the prosthetic provision.

Within/between day effect: The skin-electrode interface is influenced by a number of factors. These include, for example, sweat, temperature, and other physiological mechanisms. Fatigue and differences in donning the prosthesis can be further factors that influence intent detection. The changes introduced by these factors over the course of time are summarised in the within/between day effect.

Further challenges have been identified by Franzke et al. [15]. These include:

Process of switching prosthesis actions: In direct control, cycling through different actions using a switching command is often experienced as cumbersome. The higher the number of possible actions, the longer it takes to select a specific one. Since the focus of this thesis lies on ML-based myocontrol, which has the beneficial property of not requiring a switching command, this challenge will not be covered explicitly.

Extensive training in ML-based myocontrol: In ML-based myocontrol, the learning process can be lengthy, potentially unsuccessful and, therefore, dissatisfying. Multiple attempts might be required. Furthermore, more complex ML methods might be more sensitive to changes in the EMG signal and require recalibration at regular intervals.

With the exception of the Electrode shift effect, all of the challenges mentioned are concerned with the control of myoelectric prostheses, which is our core focus in this thesis, specifically ML-based myocontrol. We will not cover issues arising from durability, comfort of wear, appearance or level of noise, as hardware development is not part of this thesis. These issues, however, are as important as a natural control of one's prosthesis. In this context, some studies have reported haptic feedback to be a desired feature [8, 10, 19]; on the other hand, another study could not verify that [14]. Although feedback is an essential concept in this thesis, haptic feedback will not be covered here.

1.4 Contributions

The aforementioned challenges emerge from very different areas of upper-limb prosthetics. However, we believe that employing **co-adaptation** and facilitating the interaction between the user and prosthesis is key in dealing with all of them.

Co-adaptation refers to the adaptation that occurs both on the side of the ML method and on the side of the user. Using this keyword, we want to put the user in the focus of our work and put them in the loop from the beginning. A well-known issue in prosthetics regards results that have been found without the user in the loop. It has been shown that the transfer of findings without the user in the loop to usability is controversial [20, 21, 22]. Closing the loop, i.e., providing the user with live feedback on their actions, will lead to learning and adaptation on the side of the user. The fact that a user can learn to compensate for the shortcomings of a given controller might be the reason for the mismatch between offline and online findings. User adaptation is a highly desirable feature that needs to be accompanied by the potential for adaptation on the side of the ML algorithms. In this thesis, we realise this property by means of **incremental Machine Learning (iML)**.

This term covers ML methods that allow for updates of the training data and don't require full retraining, i.e. full replacement of the training data and rebuilding of the model. By updating the training data, iML methods adapt to changes and improvements on the side of the user. Regarding the **limb position effect**, for example, updates can be issued in poses where the myocontroller reaches its limits. This allows the user to start with a minimal functional training dataset, which can be extended when required. A direct connection can also be drawn to the challenge regarding **extensive training in ML-based myocontrol**. With minimal initial training and occasional updates, the overall time for training could be reduced. More details about the iML method used for the majority of the thesis can be found in Section 2.3 and specifically in Section 2.3.4.

With iML methods granting us access to co-adaptative interaction between the user and prosthesis, we approached the challenges mentioned in the previous section from three different angles in this thesis. These are **muscle signals**, **theory on user-prosthesis interaction** and **simultaneous assessment and training**. Figure 1.2 visualises this concept. Circles of different colours highlight what area of the user and their prosthesis they encompass, starting from the smallest and most specific one at the

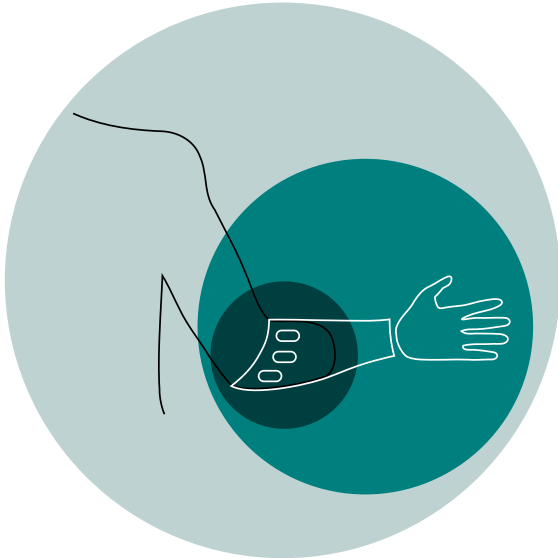


Figure 1.2: Different areas of user and prosthesis interaction addressed in this thesis. ● muscle signals: benefits of different sensors for signal detection and transparent design of the myocontroller; ● theory on user-prosthesis interaction: influence of the degree of interaction of the user with the prosthesis; ● simultaneous assessment and training: development and testing of a protocol to appropriately evaluation the usage of modern prosthetic devices

sensor level, gradually increasing to include the prosthesis at the direct interaction level and eventually leading to a holistic view of user and prosthesis at the assessment and training level.

● **Muscle Signals:** The gold standard to detect muscle signals in prosthetics is EMG. Our contribution to this area is two-fold. First, we show the validity of a different sensor type for muscle-signal detection, namely Forcemyography (FMG). This method has been investigated before, and a number of publications have highlighted the benefits of FMG, among them some of our own [n, l]. However, to the best of our knowledge, we have, for the first time, fused EMG and FMG in a user study with online goal-reaching tasks, see **Publication 1**. We were able to confirm, with the user in the loop, the benefits so far only demonstrated in offline scenarios. Furthermore, we were able to show that FMG is less prone to the **contraction intensity effect** than EMG. Interference between different actions at low levels of activation was only present for EMG and not for FMG. Second, we employ High-Density Surface Electromyography (HD-sEMG), which consists of a high number of EMG sensors arranged in a grid structure, in the implementation of a myocontroller specifically designed for robustness and intuitive use, see **Publication 2**. In a user study involving people without limb absence and a person with limb absence, we showed that an algorithm with reduced complexity and tailored towards transparency for the user showed remarkable capabilities in online goal-reaching tasks. We were able to deal with **extensive training in ML-based myocontrol** by realising Simultaneous and Proportional Control (SPC) only training on individual actions but reaching goals involving up to three DOFs at the same time in an online user study. Furthermore, this myocontroller was trained with one level of activation only and could abstract to the full range physically possible, hence, dealing with the **contraction intensity effect**. Moreover, there were no significant differences in performance between people without limb absence and the person with limb absence, which shows the potential of this approach for application in myoelectric prostheses.

● **Theory on User-Prosthesis Interaction:** The field of psychology offers manifold theories regarding learning and interaction. In **Publication 3**, we use methods from Radical Constructivism (RC) to change the perspective on prosthetic myocontrol. Within this framework, the prosthesis is seen as an entity of its own. The prosthesis is learning to understand information the user provides and builds a model of what it perceives. Where the model fails to explain the data, novel information needs to be acquired to update the model. This concept, in its essence, describes iML. In an online user study, we were able to show that the interaction between prosthesis and user indeed leads to a subjectively better controller. This, in turn, emphasises iML as an effective improvement in myocontrol, which helps deal with **extensive training in ML-based myocontrol**.

A central concept within the RC framework is perturbation, which is the experience of novel information to update one's model. We have developed an *oracle* to automatically detect these situations and trigger the interaction with the user from the prosthetic side [o, r, u]. These findings go beyond the development of the RC framework and are not directly part of this thesis.

● **Simultaneous Assessment and Training:** Finally, we address the lack of an adequate assessment and training protocol for modern ML-based prostheses by designing such a tool, the Simultaneous Assessment and Training of Myoelectric Control (SATMC). In this process, we have taken the challenges outlined in the previous section into account and put particular emphasis on the **limb position effect**, the **within/between day effect** and **extensive training in ML-based myocontrol** [h, m, s]. The result is a multi-session protocol of increasing complexity and difficulty, which is composed of tasks involving multiple actions performed in different positions. Using the SATMC, we demonstrated the effectiveness of incrementality and co-adaptation in a long-term user study involving a person with limb absence using a custom-built prosthesis with an iML-based myocontroller, see **Publication 4**. The design, according to Single Case Experimental Design (SCED), allowed us to draw conclusions with only one subject and fostered the reproduction of studies based on the SATMC.

Beyond these contributions, the myocontrol algorithm refined in the investigation of this thesis was integrated into a Virtual Reality (VR) application for rehabilitation, the Virtual Therapy Arm (VITA) system [v]. The original idea of treating Phantom Limb Pain (PLP) in VR was awarded the "DLR IDEA AWARD 2015 Leben 4.0" and funding to develop the first prototype. The successful development allowed us to secure further

(a) (b) (c) (d)

Figure 1.3: The VITA system: (a) a patient after his first experience with the VITA system; (b) the VITA logo; (c) visualisation of a patient in the VITA environment; (d) the author and a colleague of the author presenting the VITA system at the DIGITAL-X 2022 in Cologne, Germany

funding for a study that is currently being carried out in four rehabilitation institutes in Germany and Italy to validate the functionality of the VITA system to treat PLP for upper and lower limbs and support rehabilitation after a stroke [w]. Figure 1.3 shows a patient after using the VITA system, the VITA logo, a patient using the VITA system, and the author of this thesis and his colleague presenting the VITA system to the public. We have also patented the muscle-signal-based interaction in VR [k].

The work presented in this thesis demonstrates the benefits of co-adaptation enabled by iML for the control of myoelectric prostheses. With the implementation of these findings, we hope to provide a positive impact on the lives of people with limb absence.

1.5 Structure of Work

The remainder of this thesis is organised as follows. **Chapter 2** provides background for our investigations and describes in more detail what our studies are based on. This covers the fundamentals of muscles and how to measure their activity, different strategies for prosthetic control based on these signals, theoretical background on interaction and methods for assessment of myocontrol. **Chapter 3** contains a short summary of the four core publications that build this thesis. **Chapter 4** discusses the contributions of this thesis, compares them to relevant existing literature and covers their limitations. **Chapter 5** provides concluding words and an outlook on future work. In **Appendix A**, full-text versions of the core publications comprising this thesis can be found.

2 Background & Methods

Similar to most domains, upper-limb prosthetics also hosts a prestigious competition where the most advanced technical accomplishments compete against each other. It is the **Arm Prosthesis Race (ARM)** of the **Cybathlon**, which is organised by Eidgenössische Technische Hochschule Zürich (ETH Zürich) [23]. It is a series of tasks based on Activities of Daily Living (ADLs) that test dexterity, precision and reliability. Figure 2.1 shows the winners of the ARM competitions of the two Cybathlons in 2016 and 2020.

(a) **(b)**

Figure 2.1: Winners of the ARM competition of the Cybathlon: (a) Robert Radocy [24] (Winner, 2016) and (b) Krunoslav Mihić [24] (Winner, 2020)

Remarkably, although there was strong competition in modern myoelectric prostheses, the winners in both iterations were people using a body-powered prosthesis. Robert Radocy, the winner of the first Cybathlon in 2016, was eager to show what could be achieved with a body-powered prosthesis, and he and his team succeeded. The **Maker Hand** team followed in his footsteps in the second iteration of the Cybathlon in 2020.

This example shows the duality of the state of the art. Although the scientific state of the art pushes the limits of what can be achieved with technical solutions, in daily life, the usage of a reliable body-powered gripper can bring you remarkably far.

Our goal is to bring the scientific state of the art, which will be described in the following, closer to the user by employing co-adaptation through iML.

2.1 Muscles

Muscle tissue drives voluntary and involuntary motion of the human body. Since this work is centred around the intent of the user, we will focus on skeletal muscles only, which can be activated voluntarily [25]. Other types are cardiac and smooth, which can be found in the heart or the intestine, respectively [26].

The macroscopic skeletal muscle consists of three hierarchical levels of encapsulation, which go down in scale to the individual muscle cell, the muscle fibre. An image taken with an optical microscope of tissue from a skeletal muscle can be found in Figure 2.2. It shows a number of longitudinal muscle fibres in the area of the Neuromuscular Junction (NMJ). The NMJ is the location where the efferent motor neuron innervates the muscle fibre. The areal black structures in Figure 2.2 are these innervation sites, where a signal from the nervous system arrives and a muscle activation is triggered. The same motor neuron can innervate between $50 - 1000$ muscle fibres [27]. The combination of motorneuron and the muscle fibres it innervates is called Motor Unit (MU).

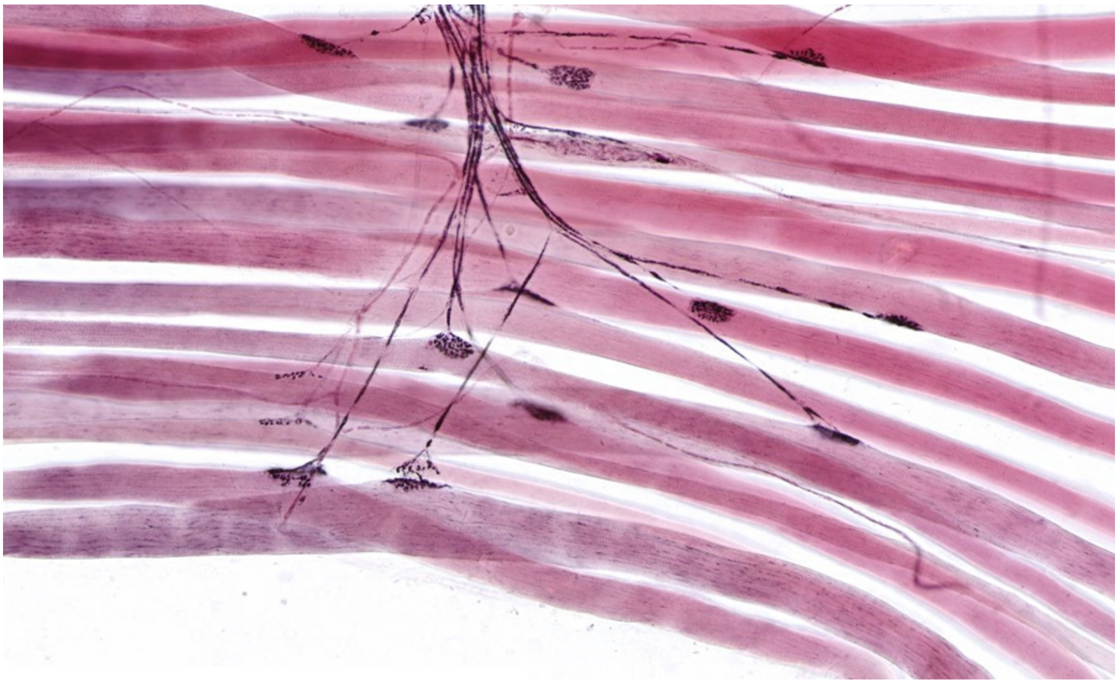


Figure 2.2: Image of muscle innervation using an optical microscope [28]: horizontal red structures are the muscle fibres; black lines are the axons innervating the muscle fibres; areal black structures are the NMJs

All fibres in a MU are of the same type, of which there are three in the skeletal muscle. These are called Type I, Type IIa and Type IIb/x, and they differ in their discharge rate and their susceptibility to fatigue [29]. Type I is slow twitching and fatigue resistant, Type IIa is fast twitching and fatigue resistant, and Type IIb/x is fast twitching and fatiguing. These types serve different purposes. Type I is predominantly involved in endurance activities, while Type IIa/b/x are rather involved in tasks requiring power. This distinction is also important when increasing the contraction of a muscle. MUs of different types are recruited in a specific order [30]. The recruitment follows two principles: Henneman's principle [31] and the Onion Skin principle [32, 33]. According to Henneman's principle, at low levels of Maximum Voluntary Contraction (MVC), small MUs are recruited first, followed by MUs of increasing size. This continues up to $50-60\%$ MVC, after which a further increase in force is realised by an increase in discharge rate. The Onion Skin principle states that MUs with high discharge frequency are recruited earlier than MUs with low discharge frequency.

When a MU is recruited, originating from the NMJ, the muscle fibre depolarises, leading to a shortening of the muscle fibre and eventually to a force along the muscle direction [26]. This shortening is based on the relative movement of two proteins in the muscle fibre, myosin and actin [34]. Due to a periodic attachment, stroke, detachment, and reconfiguration of the myosin heads, this process is called the cross-bridge cycle [35]. The depolarisation travels with $4-5m/s$ from the NMJ in both directions towards the end of the muscle fibre [36].

2.2 Measuring Muscular Activity

The most direct way of measuring muscular activity can be achieved by measuring the forces or torque at the end effector or joint created by the shortening of the muscle tissue. As this thesis is concerned with upper-limb prosthetics for people with limb absence, we have to resolve to other means.

The most common one is EMG, which frequently sees clinical application in myoelectric prostheses. FMG can be considered second to EMG as manifold studies have investigated its use in myocontrol, although no prosthetic hardware with FMG-based control has reached the market yet. These two methods and their combination are a central point in this thesis. Further methods involve Mechanomyography (MMG), Sonomyography (SMG) and Electrical Impedance Tomography (EIT).

2.2.1 Electromyography (EMG)

EMG describes the measurement of muscular activity by detecting the change in electric potential caused by the activation of the muscle. Section 2.1 described the process of activating muscles, the depolarisation of MUs and the signal propagation along the fibre. The combined signal of all fibres in a MU creates the Motor Unit Action Potential (MUAP). Since the NMJ is not in the same position for all fibres of a MU, see Figure 2.2, the superposition of the individual depolarisation signals creates a unique MUAP fingerprint [37]. The EMG signal consists of the potential of a number of different MUAPs, creating its characteristic signal due to superposition and cancellation. Figure 2.3 depicts this process. A number of the findings regarding the underlying functionality of muscles were only possible through EMG [32, 38].

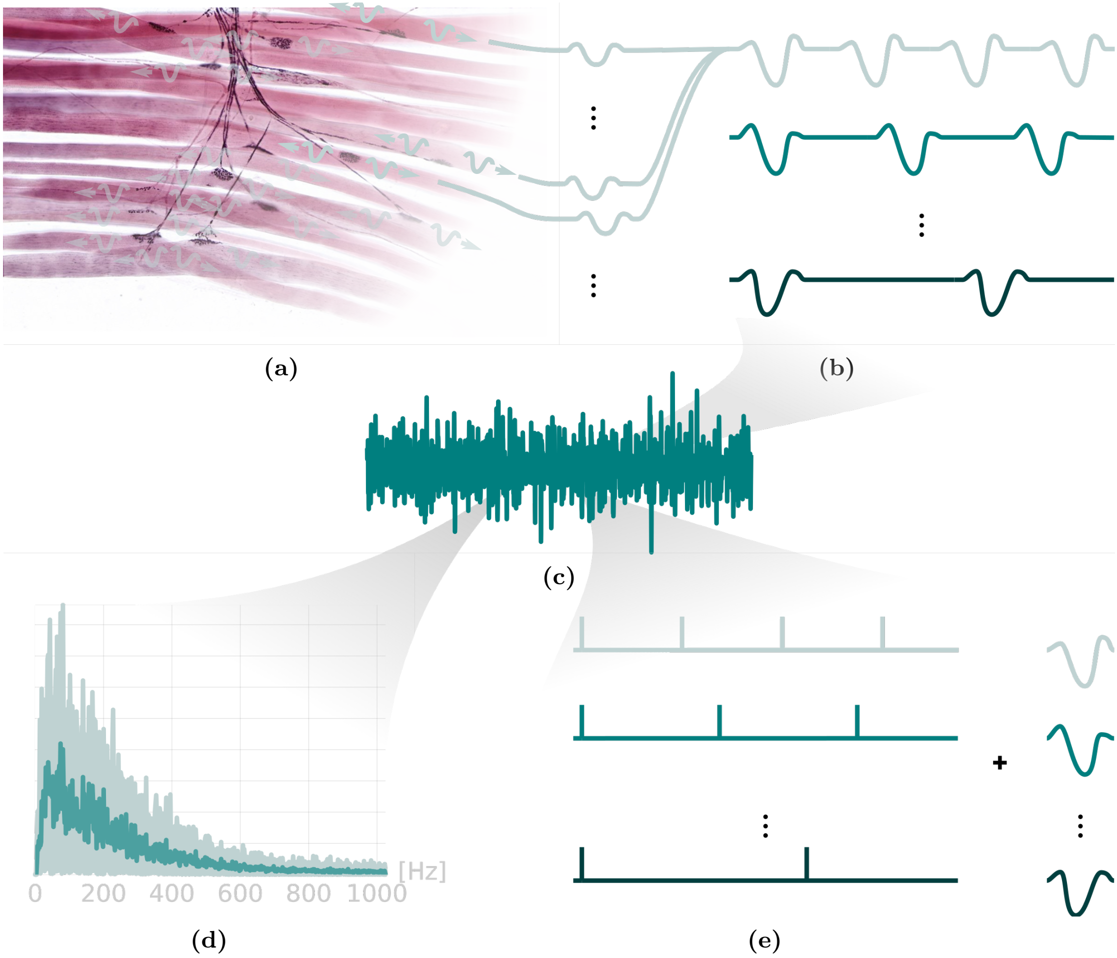


Figure 2.3: EMG-signal generation: (a) depolarisation of muscle fibres originating from the NMJs travelling along fibres; (b) superposition of individual muscle-fibre signals leads to characteristic MUAP; (c) superposition of multiple MUAPs results in the EMG signal; (d) frequency spectrum of an exemplary EMG signal sequence; (e) decomposing into spike trains and MUAPs

The EMG signal can be read **invasively** and **non-invasively**. Invasive techniques using needle or fine-wire electrodes allow targeted measurements with little cross-talk and noise [39, 40] and have been used successfully to control prostheses [41, 42, 43].

However, for daily use in prosthetic devices, measuring the EMG signal on the surface of the skin, which is referred to as Surface Electromyography (sEMG), is preferred to percutaneous approaches. Implantable electrodes [44] don't require percutaneous access and are capable of measuring at the source. They have shown better EMG-data quality compared to sEMG recordings [45]. In sEMG, the electrode measuring EMG signals is not located at the source directly and, therefore, is subjected to source mixing. Muscles of different depths beneath the sensor, as well as muscles in the general vicinity, contribute to the reading of the sensor, i.e. cross-talk [46]. Furthermore, the skin and, in general, the tissue between the muscle and the sensor act as a filter for the EMG signal. In this work, we will not go further into detail. Several remarkable publications have dealt with this topic extensively [18, 37, 47]. Additionally, the properties of a sensor contribute to the measurements. Differences exist in the type, e.g. wet or dry electrodes, or form and dimension. A recent tutorial provides a great overview of the factors influencing the EMG-signal readings [48].

In short, the sEMG signal ranges between $-5mV$ and $5mV$ with a bandwidth of $0 - 500Hz$ and a mean frequency of $70 - 130Hz$ [49]. Figure 2.3 visualises the power spectrum of the EMG signal on the bottom left.

From the EMG signal, manifold information can be extracted. Originally, this method was developed as a diagnostic tool and is still used for this purpose. Electrocardiography (ECG) might be the most widely known diagnostic tool based on the changes in the electric potential of a muscle. While ECG helps diagnose abnormalities in the heart muscle, EMG measurements do the same for neuromuscular abnormalities. These include muscular dystrophy, carpal tunnel syndrome or amyotrophic lateral sclerosis [50].

In terms of this thesis, EMG signals are used to draw conclusions about the intent of the person expressing them. As the strength of the EMG signal is proportional to the muscular activity [18], information regarding force and action can already be extracted from its envelope. However, more information can be extracted from other characteristics of the EMG signal. Regarding the use of EMG in prosthetic control, a set of four Time Domain (TD) features has been developed by Hudgins et al. [51]. Although still very common, there are a large number of additional features that have been developed for myocontrol. Phinyomark et al. [52] have reviewed 37 features for classification based on EMG data. This analysis was extended to 58 features, and using a clustering approach resulted in a topologically informed chart with recommendations of representative features [53], see Figure 2.4. With the advent of wearable EMG-sensor bracelets, a comparison was performed between conventional sensors with sampling rates $> 1000Hz$ and wearable sensors with a lower sampling rate of $200Hz$ [54]. This study suggests two feature sets for usage with low-sampling-rate sensors.

Besides the advent of wearable sensors, advancements have also been made based on spatial information of sEMG data. These investigations require a high number of sensors in a specific orientation, such as a grid, called HD-sEMG. Based on HD-sEMG, further information can be extracted, such as the decomposition of the sEMG. As a result, individual MUAPs can be extracted. Mathematically, the composition of an EMG signal x can be expressed as follows

$$\boldsymbol{x}(k) = \sum_{l=0}^{L-1} \boldsymbol{H}(l) \cdot \boldsymbol{s}(k-l) + \boldsymbol{n}(k) \tag{2.1}$$

where

$$\boldsymbol{x}(k) = [x_1(k), x_2(k), \cdots, x_m(k)]^T \tag{2.2}$$

$$\boldsymbol{s}(k) = [s_1(k), s_2(k), \cdots, s_n(k)]^T \tag{2.3}$$

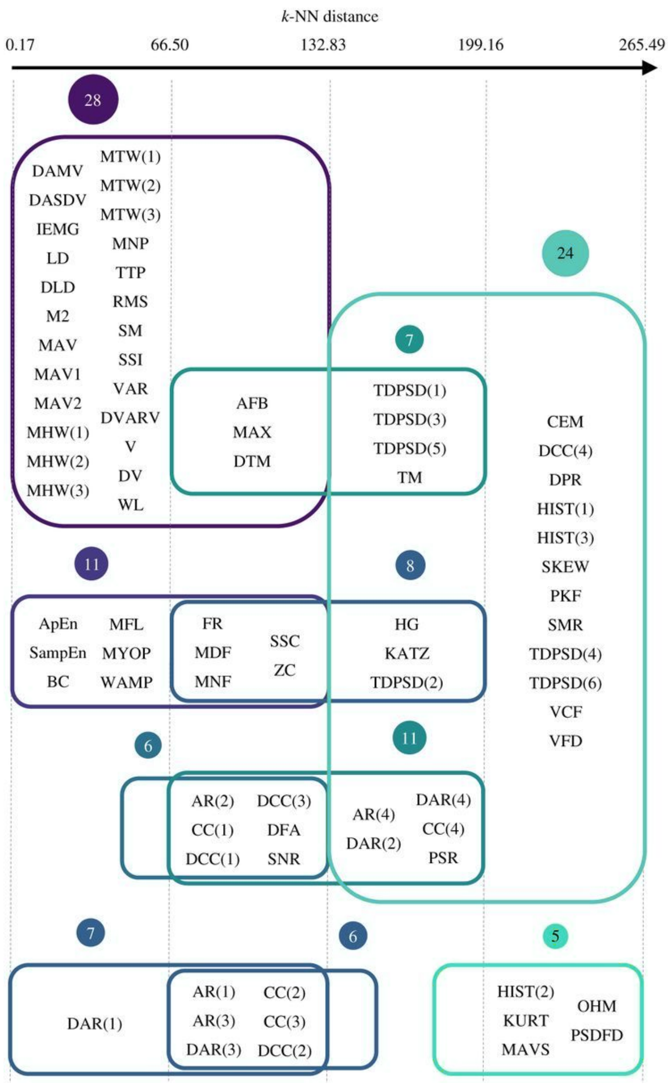


Figure 2.4: Feature map created by Phinyomark et al. [53] clustering and arranging multiple features based on their kth nearest neighbour distance; reprinted under license CC BY 4.0

$x_i(k)$ is the kth sample of the ith EMG sensor, m is the number of EMG sensors, $s_j(k)$ is the kth sample of the spike train of the jth MU, n is the number of MU and $\boldsymbol{H}(l)$ is a $m \times n$ matrix of the MUAPs with $l = 0, \cdots, L-1$ and L the length of the MUAPs. Different methods exist to identify MU spike trains. Among them are manual methods such as spike sorting using EMGLAB [55] and automatic ones based on Convolution Kernel Compensation [56], fast Independent Component Analysis [57] and their combination [58]. The accuracy of the identified MUs can be assessed using methods such as the pulse-to-noise ratio [59].

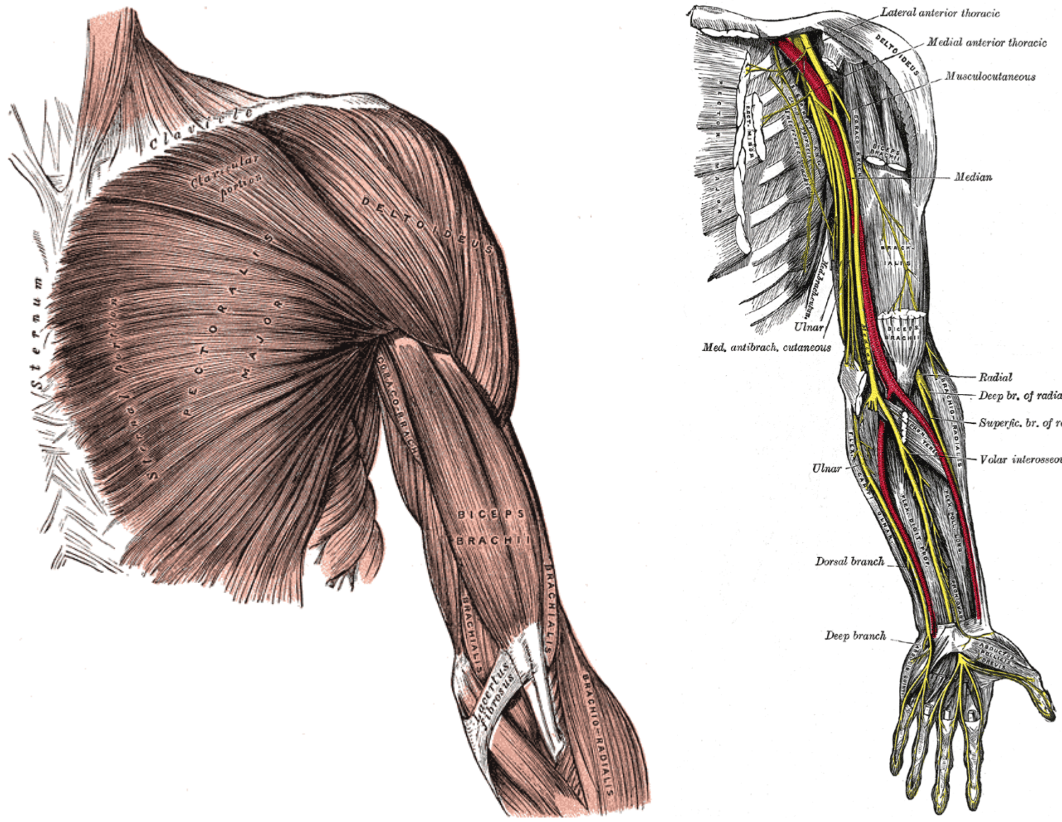
Initial work on EMG decomposition was based on invasive sensors [55, 60, 61, 62]. Due to the selective nature of invasive sensors, only a few MUs could be detected [40]. New developments allowed for decoding at the surface [39, 56, 63, 64], which, however, only allows the decomposition of superficial MUs [65]. Invasive methods have been used to validate decomposition approaches together with model-based approaches [59, 66]. Newly developed invasive high-density sensors [67] have further improved automated decomposition based on HD-sEMG [58]. EMG decomposition allows us to improve our understanding of motor control from the intent formed in the brain to the synergistic activation of MUs [68].

In a sense, the EMG signal can be seen as an encoded version of the neural information, which are the original impulses sent by the brain. Reading neural information directly is more complex since the signal is approximately three magnitudes smaller than EMG (μV vs. mV) and can not be done from the surface [49]. Therefore, the EMG signal can be seen as an amplification of the efferent neural information. In case of high levels of amputation, e.g. transhumeral or shoulder disarticulation, the muscles that controlled more distal actions, such as hand or wrist movements, might not be present any more. However, the nerves originally innervating these muscles can remain without serving a purpose. Using the example of shoulder disarticulation, the *median*, *radial*, *ulnar* and *musculocutaneous nerves* have lost the muscles to innervate and the *pectoralis major*, and *pectoralis minor muscles* have lost the limb to actuate. These muscles and nerves can be seen in Figure 2.5. Based on these considerations, a revolutionary new surgical technique was developed called Targeted Muscle Reinnervation (TMR) [69, 70, 71, 72]. During TMR, the aforementioned muscles can be denervated and reinnervated with the aforementioned nerves. This process allows the detection of the intent to move the hand and/or wrist through EMG readings of the *pectoralis muscles*. Additionally, the skin can be reinnervated as well, which is a procedure called Targeted Sensory Reinnervation (TSR) [69, 73, 74]. This procedure restores the sensation of touching parts of the lost limb at the site of reinnervation. Gaining sensation can close the loop in prosthetic control by providing haptic feedback. Additionally, TMR can lead to the reduction of neuroma pain and PLP [75, 76, 77]. Considering these aspects, TMR has become an essential step in the provision of people who have lost a limb [78].

2.2.2 Forcemyography (FMG)

Measuring muscular activity using FMG is based on the macroscopic bulging of muscles. Due to the conservation of volume, the shorting of a muscle results in an increase in its cross-section, which can be measured using a force sensor at the surface of the skin, see Figure 2.6.

Different pressure sensors have been used to measure FMG [80, 81, 82]. The introduction of robust and miniaturised *force-sensitive resistors* allowed a broader application of FMG [83, 84]. A number of studies have investigated FMG for myocontrol. Among these are studies involving FMG bracelets [85, 86, 87] or sockets with a high number of sensors [88, 89]. Xiao et al. [90] published a comprehensive overview of FMG-based developments in myocontrol.

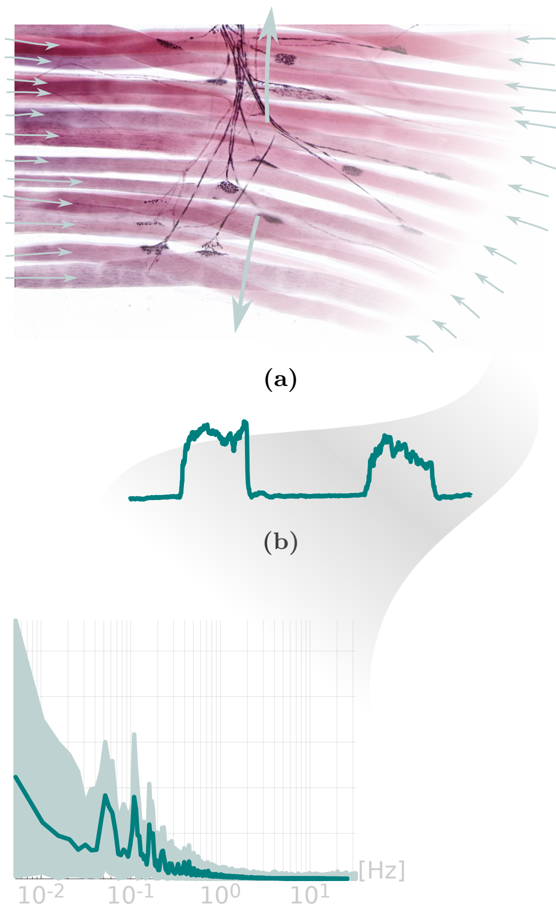


(a) **(b)**

Figure 2.5: Muscles and nerves of the upper limb: (a) focus on *pectoralis major muscle* [79]; (b) focus on *median*, *radial*, *ulnar* and *musculocutaneous nerve* [79]

Furthermore, the same group investigated the signal properties in more detail, providing insight into FMG readings [91]. The FMG signal can be measured in a number of ways, i.e. varying the material and structure in contact with the skin. Based on its properties, this layer can act as a filter and change the FMG signal characteristics. It can also lead to drift or hysteresis in the signal readings [80, 92, 93].

However, certain advantages over EMG exist [86]. FMG sensors produce signals that are more reliable, placement does not require the same precision as for EMG sensors, they are less sensitive to sweating, and they support intuitive control [94]. In general, FMG is less sensitive to the skin-sensor interface. The electrical impedance does not play a role in the measurement, which allows the user to wear clothing underneath the sensor. This property plays an important role, e.g. in industrial scenarios. Sierotowicz et al. [95] controlled an exoskeleton using FMG signals. The integration of FMG sensors in the exoskeleton that can be worn over clothing simplifies the usage of a muscle-signal-driven assistive device. Comparisons to other measures of muscular activity have been performed, demonstrating the capabilities of FMG. Ravindra et al. [96] have compared



(a) (b) (c)

Figure 2.6: FMG-signal generation: (a) muscle force generation originates from fibre shortening, which, due to the isovolumetric contraction, results in a force orthogonal to the muscle fibre; (b) raw FMG signal; (c) frequency spectrum of an exemplary FMG-signal sequence

FMG, SMG and sEMG and concluded that FMG, with its benefits in signal stability and its comparable accuracy and wearability, can be a promising alternative to sEMG. A comparison by Connan et al. [97] using a wearable acquisition device supports these findings. They focused on the comparison of signal properties and illustrated the higher signal stability of FMG.

Although superior to sEMG in the areas described above, there are other factors that influence FMG. FMG also suffers from the limb position effect, which changes the load distribution on sites where the signal is measured. Furthermore, external loads on the sensors, e.g. originating from heavy loads carried by a prosthetic hand, influence the readings directly [94].

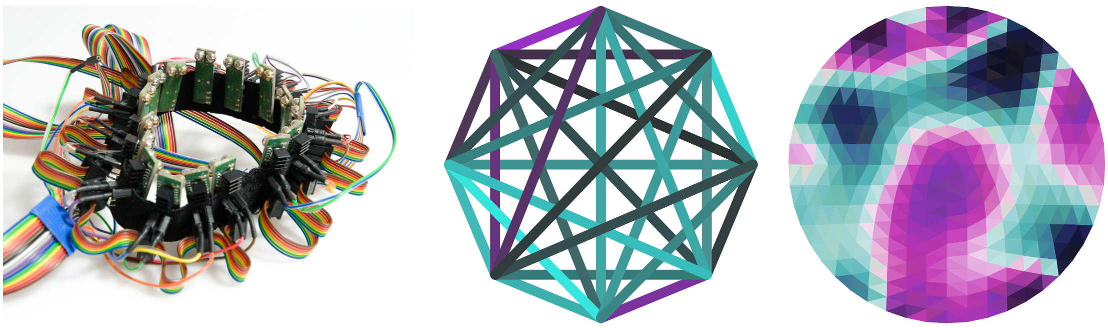
Similar to sEMG, there is a high-density version of FMG, which is known as FMG-arrays or Tactile Myography (TMG) [88, 98, 99]. This method has been studied involving people with limb absence, showing its potential for prosthetic control [92, 93].

2.2.3 Further Methods

Although only EMG and FMG have been investigated in depth over the course of this thesis, there are further interesting methods for measuring muscular activity.

We have mentioned MMG before, which measures high-frequency oscillations of the muscle due to the cross-bridge cycle [34]. The phenomenon is also known as *acoustic myography*, as it can be measured with microphones [100, 101, 102]. MMG has the beneficial feature that it can be measured through clothing [103]

Furthermore, there are methods that are of a tomographic nature. These include SMG and EIT. SMG uses ultrasound to create an image of the cross-section of the underlying tissue. It has been adapted for myocontrol [104] and was used in a study to play the harmonium [a]. A comparison of sEMG, FMG and SMG has been mentioned in the previous section [96]. EIT-based tomography relies on impedance measurements using electric currents. The circular sensor orientation spans a network, where each sensor-connecting line represents a measurement, see Figure 2.7. These individual measurements can be combined to produce a tomographic image. Based on the cross-sectional information, up to eight different actions could be detected in user studies using an EIT bracelet [105, 106, 107]. A recent study compares FMG, EIT and SMG with a particular focus on their applicability for myocontrol [108].



(a) **(b)** **(c)**

Figure 2.7: Tomography based on EIT: (a) EIT bracelet; (b) raw EIT measurements between sensors; (c) reconstructed tomographic information based on raw EIT measurements

These tomographic techniques have a higher power consumption and are larger in size. However, technical advancements in SMG have shown promising results in terms of modification towards embeddable sensors for prosthetic control [109, 110]. Furthermore, a number of wearable EIT bracelets have been developed [105, 107, 111].

2.3 Myocontrol

Myocontrol refers to the control of a device using muscle signals. This includes direct control and ML-based control (also known as *pattern recognition*).

Direct control has been introduced in Section 1.2. The main aspects are the direct use of the envelope of the EMG signal to control the opening and the closing of an action using a threshold and a switching command, e.g. coactivation, to cycle through different actions. This approach is easy to learn and transparent to the user and, therefore, reliable and robust, while the switching is cumbersome and unintuitive, see Section 1.3.

2.3.1 Sequential & Discrete

The goal of ML-based control is to provide a more natural way to control a prosthetic device. Early work mentioned the benefits of natural control and introduced the previously mentioned TD feature set or *Hudgins features* [51]. Their approach was based on an Artificial Neural Network (ANN) and was later adapted by investigating features from the Time-Frequency Domain (TFD) and changing the classifier to an Linear Discriminant Analysis (LDA) classifier [112]. Further improvements led to the myocontroller, which has been the foundation of prosthetic myocontrol up until today [113, 114]. It is based on four TD features and an LDA classifier.

The **Mean Absolute Value (MAV)** estimates the mean absolute value of a window of N samples of an EMG measurement x_i.

$$MAV = \frac{1}{N}\sum_{i}^{N} |x_i| \tag{2.4}$$

The **Zero Crossings** is a frequency measure based on the oscillating character of the EMG signal. A threshold was introduced to distinguish the measure from noise and was set to $x_{\text{th}} = 2\mu V$ in the original publication [51].

$$ZC = \sum_{i}^{N-1} f(x_i \cdot x_{i+1}) = \begin{cases} 1 & \text{if } x_i \cdot x_{i+1} < 0 \text{ and } |x_i - x_{i+1}| > x_{\text{th}} \\ 0 & \text{else} \end{cases} \tag{2.5}$$

The **Slope Sign Changes** is a frequency feature measuring changes in the waveform, similar to the Zero Crossings. A threshold aims at distinguishing noise from signal with $z_{\text{th}} = 2\mu V$ [51].

$$SSC = \sum_{i=2}^{N-1} f([x_i - x_{i-1}] \cdot [x_i - x_{i+1}]) \quad \text{with} \quad f(z) = \begin{cases} 1 & \text{if } z > z_{\text{th}} \\ 0 & \text{else} \end{cases} \tag{2.6}$$

The **Waveform Length** is a complexity measure of the waveform based on the cumulative length of the EMG signal.

$$WL = \sum_{i}^{N-1} |x_i - x_{i+1}| \tag{2.7}$$

The LDA method seeks to find a projection that maximises the relative class distance, see Figure 2.8. For this purpose, a cost function is minimised, which is defined as follows

$$J(\boldsymbol{W}) = \frac{|\boldsymbol{W}^T \cdot \boldsymbol{S}_B \cdot \boldsymbol{W}|}{|\boldsymbol{W}^T \cdot \boldsymbol{S}_W \cdot \boldsymbol{W}|} \tag{2.8}$$

with

$$\boldsymbol{S}_W = \sum_{i}^{c} \sum_{\boldsymbol{x} \in \text{class}_i} (\boldsymbol{x} - \boldsymbol{\mu}_i) \cdot (\boldsymbol{x} - \boldsymbol{\mu}_i)^T \tag{2.9}$$

$$\boldsymbol{S}_B = \sum_{i}^{c} n_i (\boldsymbol{\mu} - \boldsymbol{\mu}_i) \cdot (\boldsymbol{\mu} - \boldsymbol{\mu}_i)^T. \tag{2.10}$$

$\boldsymbol{W}$ is the projection matrix, $\boldsymbol{S}_W$ the within-class scatter, $\boldsymbol{S}_B$ the between-class scatter, $\boldsymbol{x}$ the EMG data, $\boldsymbol{\mu}$ the data mean, $\boldsymbol{\mu}_i$ the class mean, c the number of classes and n_i the number of samples in a class.

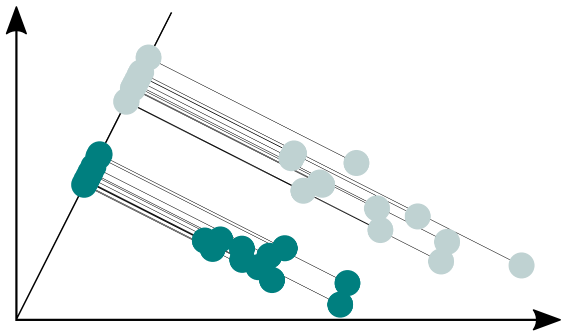


Figure 2.8: Visualisation of the projection determined using LDA based on [d]

Besides LDA, a number of different classification methods are common algorithms to detect the user's intent. Overviews can be found in a number of review articles [10, 49, 115, 116]. Among these classification methods are further LDA variants [114, 117, 118], ANN/Multi-Layer Perceptron (MLP) [51, 117, 119], fuzzy logic [120, 121, 122, 123], Support Vector Machine (SVM) [117, 124, 125, 126, 127], Hidden Markov Model (HMM) [128, 129], and Gaussian Mixture Model (GMM) [130, 131]. These approaches used manifold features of the EMG signal. They can be divided into TD, Time-Serial Domain (TSD), Frequency Domain, and TFD [49]. A remarkable overview has been published by Phinyomark et al. [53], which we have mentioned before, see Figure 2.4. The vast majority of these and similar studies managed to achieve a recognition rate of $> 95\%$, distinguishing eight or more different actions. To a large extent, these studies were evaluated *offline*. This term refers to collecting a dataset, performing all processing steps, splitting the dataset, tuning and training a model with one part and testing it with the other. Early studies aimed at improving and optimising offline measures, which yielded almost perfect classification.

2.3.2 Simultaneous & Proportional

The results mentioned in the last section, which date back more than ten years, are in stark contrast with the initial quote of the thesis and the results of the Cybathlon outlined at the beginning of this chapter.

New concepts were developed, and SPC became an important keyword [132]. The rationale was that classification-based control with discrete action detection does not resemble natural control. Contrary to discrete actions, continuous proportional activations and their simultaneous combination do so more closely. Proportionality can be added to classifiers, e.g. by calculating the power of the EMG signals [133, 134]. Even simultaneous activations can be achieved in combination with classification methods [135, 136]. However, this requires training combined activations, which is feasible for two-DOF combinations but starts to become demanding with three-DOF combinations [135].

This gave rise to regression-based control algorithms. Particularly, Non-negative Matrix Factorisation (NMF) [137], a semi-supervised decomposition method, showed promising results. Jiang et al. [132] derived the NMF approach from EMG-signal generation based on muscle synergies [138] to realise SPC of two DOFs. The intended actions $y_j(t) \in \mathbb{R}$ are mapped through synergy gains s_{ij} into muscle activations $m_i(t)$

$$m_i(t) = \sum_{j=1}^{N} s_{ij} \cdot y_j(t) \tag{2.11}$$

assuming a linear instantaneous mixture

$$\begin{aligned} x_k(t) &= \sum_{i=1}^{M} g_{ki} \cdot m_i(t) && (2.12)\\ &= \sum_{j=1}^{N} \left(\sum_{i=1}^{M} g_{ki} \cdot s_{ij} \right) y_j(t) && (2.13)\\ &= \sum_{j=1}^{N} w_{kj} \cdot y_j(t) && (2.14) \end{aligned}$$

with the kth sensor reading $x_k(t)$, the attenuation factor for the kth sensor and ith muscle g_{ki} and the resulting weights w_{kj}. In matrix notation Equation (2.14) can be rewritten as

$$X(t) = W \cdot Y(t). \tag{2.15}$$

W can be determined using NMF and a training procedure proposed by Jiang et al. [132]. Each DOF involved is trained individually by activating it in both directions, e.g. wrist flexion/extension. This leads to following expression for W and $y_j(t)$

$$\begin{aligned} X(t) = {}&[W_1^+, W_1^-, W_2^+, W_2^-, \cdots, W_D^+, W_D^-]\\ &\cdot [y_1^+(t), y_1^-(t), y_2^+(t), y_2^-(t), \cdots, y_D^+(t), y_D^-(t)]^T. \end{aligned} \tag{2.16}$$

Finally calculating $W^\dagger$, the Moore-Penrose pseudoinverse of W, leads to an expression for the intended actions $Y(t)$.

$$Y(t) = W^\dagger \cdot X(t) \tag{2.17}$$

The assumption of linear instantaneous mixture was proven experimentally, and it was shown that the approach is robust to sensor shift and reduction [139]. Furthermore, this approach was successfully tested in an online scenario with people with limb absence [140, 141]. Besides NMF, further regression-based algorithms have been investigated; among them were Support Vector Regression (SVR) [142], Linear Regression (LR) [143, 144], incremental Ridge Regression with Random Fourier Features (iRRRFF) [c, j, q, u], ANN [145, 146, 147, 148] and Probability-Weighted Regression (PWD) [149, 150].

For any of these algorithms, gathering relevant ground truth or target values is essential. Since measuring forces or joint angles ipsilateral is infeasible, an option is to perform bimanual actions and use the contralateral measurements as ground truth [145, 148, 151]. However, it was shown that the quality of these mirror movements suffers from a large variance [144]. As an alternative approach or in the case of bimanual limb absence, visual cues can be used for training. These can be continuous, e.g. following a trajectory [136, 152, 153, 154], or discrete, e.g. maintaining a contraction level of a specific action for a certain amount of time [u, j, q]. Hagengruber et al. recently investigated the impact of different ways to acquire ground truth [155]. Both cue-based and mirror-movements-based training can suffer from synchronisation issues, such as a delay due to the reaction time of the user [156, 157]. Here, semi-supervised methods such as NMF have an advantage. The training procedure by Jiang et al. [132] does not require individually labelled data points but rather identifies the components of the input data that compose the two directions of a DOF.

With a suitable ground truth, regression-based algorithms can demonstrate advantages over classification-based algorithms. From a clinical point of view, regression-based myocontrol is seen as very promising due to the natural control modality they provide [158]. The benefit of a natural combination of DOF activations comes with physiological constraints. It has been shown that an action of two or more DOFs is not equal to the vector sum of the individual DOFs [j, 93]. To deal with this issue, a notion of extending the training data by adding artificially created multi-DOF data points was proposed [j]. This technique, named Linearly Enhanced Training (LET), was applied to different sets of DOFs [j, i, 159].

While the possibility of naturally combining actions is a benefit of regression-based myocontrol, the stability of single-DOF action detection is the one of classification. Hence, efforts have been taken to combine both of these methods. Amsüss et al. have combined a classifier based on common spatial patterns [134] with an LR algorithm [160]. Both methods ran in parallel, and a measure was used to determine whether a single- or double-DOF action was more likely and provided continuous interpolation between the two methods. This approach required only single-DOF training data and resulted in improved performance compared to the classifier without any additions in an online user study involving people with limb absence.

2.3.3 Closing the loop

In upper-limb myocontrol, the vast majority of approaches use batch learning. This refers to a single initial data acquisition followed by algorithm training followed by myocontrol usage. Incremental approaches can update an already trained algorithm with new training data samples. Whether incremental updates can be performed depends on the ML method. LR can be incrementally updated using the Sherman-Morrison-Formula [161]. Further methods can be incrementally updated in this manner, see Section 2.3.4. Incremental updates of these linear and non-linear approaches have found application in upper-limb myocontrol [104, q, 162]. Not only EMG-based approaches but also myocontrol based on FMG have shown promising results using incremental updates [163], where detrimental influences of the limb position effect were counteracted with regular updates to maintain a high classification rate of 98.75%.

Similar to incrementally adding new samples, algorithms can be modified to be capable of *forgetting* older samples. By introducing a forgetting factor, the weights of older samples can be reduced, effectively putting more emphasis on new data. Combining exponentially growing weights with LR results in *exponentially weighted Recursive Least Squares* [164]. This method and modifications thereof have been successfully applied to upper-limb prosthetic control [165, 166].

The aforementioned studies involve unsupervised updates of the myocontroller. However, updates can also be triggered on-demand. Doing so takes advantage of the user in the loop. Usually, updates are required when the algorithm does not perform the way the user intended. Exploiting the knowledge of the user in this scenario by offering the possibility to interact with the control system can be an improvement for myocontrol.

The updates issued by the user are a form of incrementality as well. However, this definition is softer than the one given above. Whether new samples are added through an incremental update or through full retraining of the ML algorithm is mostly a question of resources. Even providing the user with the option of performing a full retraining has improved myocontrol. Comparisons between ML-based myocontrol and direct control have been performed, showing that home trials over an extended amount of time with the option to recalibrate the prosthesis yield better functional outcomes [167, 168, 169].

With this notion, the aforementioned *forgetting* can also be simplified. When updating a myocontroller with a new repetition of a certain action, previous repetitions become obsolete since the user has learned and improved [170]. Assuming enough storage space for all training data is available, the structure becomes equivalent to that of a *ring buffer*. The addition of a new repetition, therefore, results in the removal of the oldest one of that action. This simplification allows ML methods that are not capable of incremental updates or forgetting to benefit from the interaction with the user if the required resources are available. These concepts are visualised in Figure 2.9.

We combined the aforementioned simplified incrementality and the aforementioned simplified forgetting with the ML method described in the next section and used the resulting myocontroller to perform a long-term user study involving a person with limb absence, see Publication 4.

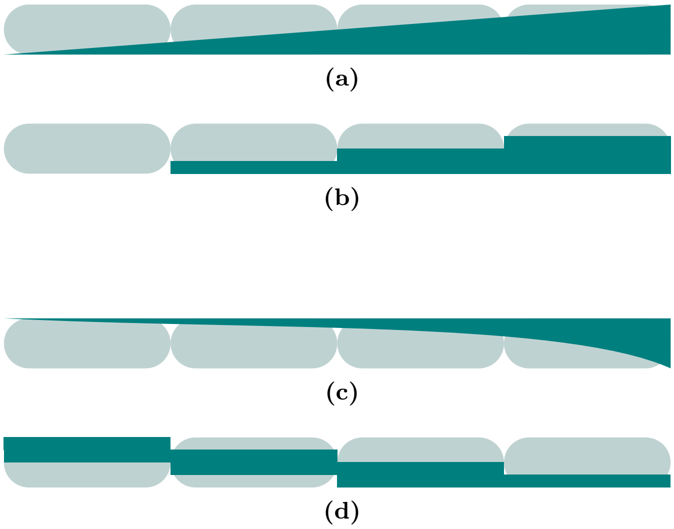


Figure 2.9: Visualisation of incrementality and forgetting. Rounded shapes are repetitions, and the remaining ones represent the amount of training data used (or the weights in (c) case): (a) sample-wise continuous incremental addition of data; (b) repetition-wise discrete incremental addition of data; (c) sample-wise exponential increase of weights; (d) repetition-wise addition of a new repetition and removal of an old one

2.3.4 Incremental Ridge Regression with Random Fourier Features

The myocontroller used in the majority of the studies performed in this thesis is iRRRFF. Fundamentally, iRRRFF is based on regularised LR or Ridge Regression (RR) [171], which can be expressed as follows

$$\hat{y} = \boldsymbol{w}^T \boldsymbol{x}. \tag{2.18}$$

Given the input $\boldsymbol{x}_i \in \mathbb{R}^d$ and the output $y_i \in \mathbb{R}$, the projection vector $\boldsymbol{w}$ can be found using

$$\arg\min_{\boldsymbol{w}} \, (\boldsymbol{X}\boldsymbol{w} - \boldsymbol{y})^2 + \lambda \|\boldsymbol{w}\|^2 \tag{2.19}$$

which yields the closed-form solution

$$\boldsymbol{w} = (\boldsymbol{X}^T \boldsymbol{X} + \lambda \boldsymbol{I})^{-1} \boldsymbol{X}^T \boldsymbol{y} \tag{2.20}$$

with $\boldsymbol{X} = [\boldsymbol{x}_1, \cdots, \boldsymbol{x}_n]^T$ and $\boldsymbol{y} = [y_1, \cdots, y_n]^T$, n the number of training samples, λ the regularisation parameter and $\boldsymbol{I}$ the identity matrix.

RR can be extended using a kernel, resulting in Kernel Ridge Regression (KRR) [172, 173]. A common choice for kernel functions are Radial Basis Functions (RBF),

$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = e^{-\gamma \|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2} \quad \text{for} \quad \gamma > 0 \tag{2.21}$$

with $\gamma = \frac{1}{2\sigma^2}$ and σ^2 the variance of the Gaussian. However, due to the kernel function, the computational cost becomes dependent on the number of samples n, which increases with incremental updates. This can become an issue in real-time applications. However, the potentially infinite feature space of a kernel can be approximated with a set of *Random Fourier Features* under specific conditions [174],

$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \langle \phi(\boldsymbol{x}_i), \phi(\boldsymbol{x}_j) \rangle \approx \boldsymbol{z}(\boldsymbol{x}_i)^T \boldsymbol{z}(\boldsymbol{x}_j) \tag{2.22}$$

For the RBF, these features take the following form

$$\boldsymbol{z}(\boldsymbol{x}) = \frac{1}{\sqrt{D}}[z_1(\boldsymbol{x}), \cdots, z_D(\boldsymbol{x})]^T \qquad \text{with} \qquad z_k(\boldsymbol{x}) = \sqrt{2}\cos(\boldsymbol{\omega}_k \boldsymbol{x} + \beta_k) \tag{2.23}$$

with $\boldsymbol{\omega} \sim \mathcal{N}(0, 2\gamma)$, $\beta \sim \mathcal{U}(0, 2\pi)$ and hyperparameter D, the dimensionality of the feature space. For convenience and to follow the established nomenclature, we will, from now on, use $\phi(\boldsymbol{x})$ as follows

$$\phi(\boldsymbol{x}) = \sqrt{\frac{2}{D}} \begin{bmatrix} \cos(\boldsymbol{\omega}_1 \boldsymbol{x} + \beta_1) \\ \vdots \\ \cos(\boldsymbol{\omega}_D \boldsymbol{x} + \beta_D) \end{bmatrix}, \tag{2.24}$$

which results in the following expression for $\boldsymbol{w}$ the projection vector

$$\boldsymbol{w} = (\boldsymbol{\Phi}^T \boldsymbol{\Phi} + \lambda \boldsymbol{I})^{-1} \boldsymbol{\Phi}^T \boldsymbol{y} \tag{2.25}$$

$$= \boldsymbol{A}^{-1} \boldsymbol{b} \tag{2.26}$$

with $\boldsymbol{\Phi} = \phi(\boldsymbol{X})$, $\boldsymbol{A}^{-1} = (\boldsymbol{\Phi}^T \boldsymbol{\Phi} + \lambda \boldsymbol{I})^{-1}$ and $\boldsymbol{b} = \boldsymbol{\Phi}^T \boldsymbol{y}$. Based on Equation (2.25), incremental updates can be performed using the Sherman-Morrison-Formula [161] for rank-1 updates of $\boldsymbol{A}^{-1}$,

$$\boldsymbol{A}_{n+1}^{-1} = \boldsymbol{A}_n^{-1} - \frac{\boldsymbol{A}_n^{-1} \cdot \boldsymbol{\phi}_{n+1} \cdot \boldsymbol{\phi}_{n+1}^T \cdot \boldsymbol{A}_n^{-1}}{1 + \boldsymbol{\phi}_{n+1}^T \cdot \boldsymbol{A}_n^{-1} \cdot \boldsymbol{\phi}_{n+1}}. \tag{2.27}$$

iRRRFF, as defined above, is a non-linear regression algorithm that can be updated incrementally. Its efficiency for myocontrol has been shown by Gijsberts et al. [c]. This method has mostly been used with the envelope of the EMG signal as the singular feature. Specifically, the Root Mean Square (RMS) was used, which falls in the same feature category as the MAV [53]. Envelope-based features are commonly used in clinical practice. It has been shown that the majority of discriminatory power in the Hudgins feature set stems from the MAV [175]. However, the extension to any feature set is possible.

2.3.5 Sensor Fusion

With manifold methods of measuring muscular activity at hand, fusing different modalities is a natural consideration. Extending EMG with another sensing method is the most common approach and an essential research direction in prosthetic control.

A number of excellent reviews on sensor fusion have been published recently with a focus on intent detection [176], specific to upper-limb prosthetics [177] and covering fusion in hand rehabilitation [178].

Among the most common extensions to EMG-based myocontrol that also reads muscular signals is FMG. A notable contribution to this topic is the prosthetic design for the Cybathlon 2016, containing both sEMG and FMG sensors [89]. In that study, a prosthetic socket was equipped with 37 FMG[1] and two sEMG sensors. Using a dynamic training procedure and an offline data analysis, Ahmadizadeh et al. showed that high accuracy using FMG signals can be reached, and fusion of FMG and sEMG leads only to a small and non-significant increase in accuracy. Other studies have come to similar conclusions about little improvement in fusing FMG and sEMG compared to sEMG [97, 179, 180]. However, a study involving a custom-designed bracelet with co-located FMG- and sEMG-sensors showed significant improvements in a fused approach compared to either method individually [181]. All these results have been obtained in offline analyses, and only a few online results are available in upper-limb prosthetics [n] compared to other domains [182, 183, 184]. We have investigated this topic ourselves and contributed to existing knowledge on fusing sEMG and FMG [n, l]. The investigations led to an online user study to validate the aforementioned offline findings, see Publication 1.

sEMG and FMG are both modalities that measure muscular activity at the surface of the skin. An interesting option for fusion is the addition of modalities that can measure information for deeper structures. This can be achieved, e.g. with tomographic modalities such as EIT or SMG, see Section 2.2.3. The fusion of sEMG and SMG has been shown to outperform unimodal approaches [185] and to provide higher resistance against fatigue than sEMG [186]. The development of co-located sensors can further advance the applicability of the fusion of sEMG and SMG [187].

The modalities described so far measure muscular or physiological information. Fusion, however, can extend further and include non-physiological sensor modalities, such as Inertial Measurement Units (IMUs) and vision. The addition of IMU signals has shown promising results for intent detection [188, 189], specifically in dealing with the limb position effect [17, 190, 191]. Furthermore, sEMG signals combined with acceleration information have proven effective in sign-language recognition [129].

Besides what types of sensor modalities to fuse, there is a further aspect to the topic of sensor fusion, i.e. how to fuse these sensors. Bao et al. [192] have analysed multiple fusion studies and identified three distinct approaches. These are feature combination, parallel processing and cascading prediction. A visual representation can be found in Figure 2.10. Parallel processing has been applied in teleoperation tasks. Connan et al. [193, 194] have realised direct bimanual pose teleoperation of a humanoid robot based on IMUs and hand action control using sEMG. A cascading approach has been used to deal with the limb position effect. Fougner et al. [191] have used IMU information to determine the limb position to subsequently switch between different classifiers trained with data from the

[1]Multiple sensor configurations were tested in this study. The one involving sEMG sensors used 37 FMG sensors. The maximum number of FMG sensors was 58.

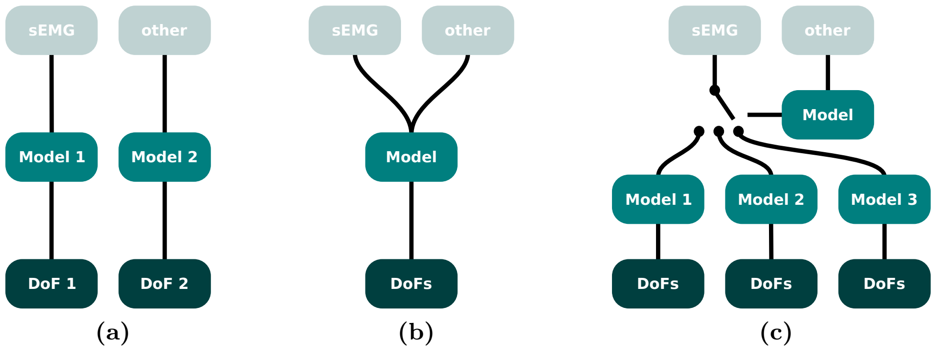


Figure 2.10: Different types of multi-modal fusion in myocontrol [192]: (a) parallel processing; (b) feature combination; (c) cascading prediction

determined limb position. In Publication 1, among other aspects, we investigate different types of feature combinations for sEMG and FMG.

2.4 Theory of Interaction

The previous section has provided an overview of methods used for controlling prosthetic devices. To a large part, we have described these methods not taking the person using them into account. This section will specifically deal with the interaction between the wearer and the prosthesis.

2.4.1 Embodiment

The integration of a prosthetic arm (among other objects) into one's body representation is referred to as *embodiment* [195]. A phenomenon that can be demonstrated with a number of objects, famously illustrated by the *rubber hand illusion* [196]. Embodiment can support people with limb absence in learning to control a prosthesis and result in a higher level of satisfaction [197].

Besides improved acceptance of prosthetic devices, embodiment can have further beneficial outcomes for people with limb absence. After an amputation, up to 80% of people suffer from PLP [198]. One explanation of this neuropathic pain places its origin in cortical reorganisation due to the missing limb [199, 200]. The embodiment of an artificial limb can help in alleviating PLP by closing the visual feedback loop [201]. Among the many treatments, *mirror therapy* is a well-known approach to treat PLP [202]. By mirroring the present limb onto the side of the absent limb, the optical illusion of a whole-body image is created. The embodiment of this image and activations involving both limbs are likely the pathway that leads to the reduction of PLP. However, a consensus has not yet been reached in the community regarding the origin and treatment of PLP [203].

The aforementioned phenomenon of a closed-visual-loop activity can be transferred into the virtual realm. In VR, the same optical illusion can be created and furthermore enhanced by using myocontrol methods [204]. A number of examples exist, among them a development of our own [v, w] that is currently in clinical evaluation to demonstrate its effectiveness. Furthermore, the usage of a myoelectric prosthesis has similar effects. The embodiment of a prosthetic limb coupled with myocontrol draws on the same underlying principle and, therefore, can also lead to a reduction of PLP.

However, a true embodiment of a prosthetic device can have further implications. Bottlenecks in the embodiment of technology have been described [205], among them maladaptive plasticity [206] and effects of the comprehensive embodiment of a prosthetic device. Would such a level of embodiment also lead to the sensation of pain through the device or due to its breakage?

2.4.2 Radical Constructivism

Prosthetic devices can also be approached differently. Instead of taking the view of embodying the prosthesis into one's own body image, the prosthesis can be seen as a tool or even as an entity of its own. Indeed, the view of a prosthesis as one's own limb has been challenged [207]. In terms of a human-centred approach, constructivist theories have been suggested [208].

The theoretical background of RC was developed starting in the 1980s by Ernst von Glasersfeld [209, 210]. This philosophical concept is concerned with nothing less than the view of the world. It is a concept contrary to *realism*, for example, where learning about the world is based on discovering the real qualities of things. Each new piece of real information helps build a model of the world, which eventually leads to an independent truth about the world. RC, on the other hand, is built on the notion that each piece of new information about the world has been perceived and, through this process of perception, subjectively influenced. In other words, everything we know about the world has been socially influenced, and reality can not possibly be discovered independent of human interpretation.

This concept can not only be used for human learning but also for ML. Fundamentally, an ML algorithm processes perceived data to build a model of its world. The purpose is to *recognise patterns*, an essential concept in RC [209] and a common term for ML [211]. The internal model is constantly challenged. New information that is perceived and does not agree with the model will lead to a reevaluation of said model and result in an updated version of it. This perturbation resembles incremental updates in ML.

The RC concept fits the notion of iML very well. Therefore, the rich learning theory of RC can be applied to iML to improve interaction in ML. In prosthetic control specifically, the prosthesis equipped with an iML-based myocontroller can be seen through the glass of the RC framework. It builds a model of what it perceives, which are the signals expressed by the person wearing the prosthesis. This approach provides a different view on embodiment than previously described. It expands it by adding the ability to interact and a certain level of autonomy to the prosthetic tool. This potentially changes how a prosthesis would be embodied towards a view as an extended semi-autonomous tool that one still has agency over. In this context, the RC framework can provide a structured methodology for the topic of interaction in prosthetic control.

The idea of combining RC and iML has been theorised before [212]. However, we have applied RC to prosthetics for the first time in an online user study involving the incremental algorithm outlined in Section 2.3.4, see Publication 3.

2.5 Assessment

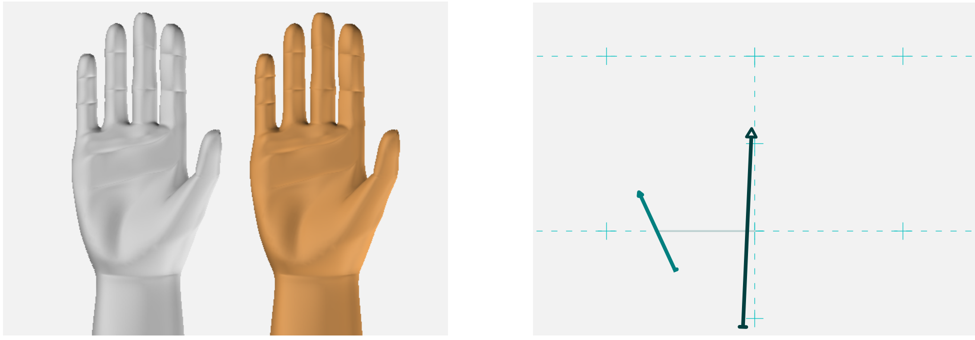
Evaluating the functionality of a prosthetic system is an essential step in the development of novel approaches. Calculating measures to compare results in combination with statistical testing enables well-founded scientific advancements. However, the situation in prosthetic control is more nuanced and requires a larger toolbox.

2.5.1 Scientific Results

In the field of myocontrol, a large part of the body of research has been done on the development of feature sets (Section 2.1) and ML algorithms (Section 2.3). Novel developments in both of these areas can be assessed by applying the methods to a given dataset, e.g. the Ninapro data [213], and comparing measures of classification rate for classifiers, goodness of fit for regressors, e.g. R^2 or Root-Mean-Square Error (RMSE) [211], or data clustering properties for features, e.g. Mahalanobis distance or Fisher's separability.

Assessing a myocontroller using these means provides insights purely from an ML point of view. However, pure offline analyses are not enough. Early studies noted that accuracy did not necessarily result in usability [133, 214]. This issue, alongside the discrepancy between research and clinical practice, led to the question of whether there is a need to change focus [20]. This discrepancy refers to the fact that there were neither any ML-based prostheses on the market at that time nor were myoelectric prostheses using direct control very popular, while numerous results were extremely promising. Further studies showed that, indeed, offline results do not necessarily translate to online usage [152, 215, 216]. Investigations concerned with this lack of correlation are still ongoing, and potentially useful offline measures are being investigated [217].

Therefore, the online and real-time tests became the standard for the evaluation of ML-based myocontrol algorithms [70, 133, 214, 218, 219, 220, 221]. Virtual or on-screen environments to perform goal-reaching tasks [104, 133, 218, 220] were developed. Figure 2.11 depicts two examples where targets are displayed on a screen, and the user has to reach them. The environment on the left shows two hands, one target and one controlled in real-time by the user. The goal for the user is to match the two actions. The visualisation on the right is more abstract. Two arrows are displayed, and the goal for the user is again to match them while they control different properties of the arrow, e.g., rotation or size, by performing a specific action. In order to successfully reach a target, a certain action has to be maintained for the dwelling time t_D and with an error smaller than a threshold e_{th}. Based on these goal-reaching tasks, measures to assess the performance have been developed [152, 222]. They involve:



(a) (b)

Figure 2.11: On-screen environments to perform goal-reaching tasks: (a) two hand models, where the grey one demonstrates the goal action and the beige one is controlled by the user; (b) the lighter of the two arrows displays the goal configuration, while the properties (angle, position, size) of the darker arrow are controlled by the user

The **Success Rate (SR)** is the ratio between the number of successfully reached goals and the number of all tasks.

The **Task Completion Time (TCT)** is the duration from the beginning of the task until a goal has been successfully completed.

The **Overshoots (OV)** is the number of instances per task where the goal area (error $< e_{th}$) was reached but was exited again before t_D was reached.

The **Speed (SP)** is the ratio between the length of the path travelled and TCT.

The **Path Efficiency (PE)** is the ratio between the shortest path from the start to the goal and the length of the path travelled.

The **Throughput (TP)** is a further measure of efficiency, taking the task difficulty I_d [223] and TCT into account.

$$TP = \frac{I_d}{TCT} \qquad \text{with} \qquad I_d = \log_2\left(\frac{D}{2 \cdot e_{th}} + 1\right) \tag{2.28}$$

with D the distance to the target.

These online and real-time tests can be collected under the term Target Achievement Control (TAC). They have become the gold standard in assessing novel developments in myocontrol in laboratory conditions due to the ease of their implementation in a virtual or on-screen environment.

2.5.2 Functional tests

A more comprehensive way of assessing novel developments involves not only the user and the myocontrol algorithm but the prosthesis as well. Tools that do so aim at the functional assessment of the user with their prosthetic provision.

Numerous assessment protocols exist in the area of prosthetic hand control. A recent overview has been provided by Kyberd [224]. Among the most common tests for prosthetic control are the Assessment of Capacity for Myoelectric Control (ACMC) [225], the Southampton Hand Assessment Procedure (SHAP) [226], the Clothespin Relocation Task (CRT) [227], and the Box and Blocks Test (BBT) [228].

The ACMC is an observational assessment tool for prosthetic usage. The person administering the ACMC has to have undergone training to do so in a proper manner. Being based on the observation of the user brings the advantage that the ACMC can be performed in the home of the user. In case this is not desired or feasible, a room specifically designed to provide a household environment can be an alternative. Being able to observe a user in an environment as close as possible to daily living provides highly relevant insights into the validity of a given prosthetic system since the activities are very close to the ones the user would engage in in daily life. The aim of observing a user in a natural environment allows only for a few restrictions or little structure to be provided to the user. This aspect complicates objective measurements and makes repeatability across a number of users more difficult. Specific guidelines have been developed and validated to increase inter-rater reliability. Although the natural environment constitutes a major advantage of the ACMC test, it has not been designed to be used with multi-articulated prostheses in its current version, and it is not encouraged to do so [224]. Additionally, requiring training of the experimenter to properly assess a person increases the difficulty of applying the ACMC test.

The SHAP, on the other hand, is a test that can be administered with minimal training of the experimenter and only requires a suitcase of objects for its execution. The SHAP includes several tasks devised to assess the capabilities of a user with their prosthetic hand. These tasks are abstractions of ADLs, and they are evaluated based on the time a user takes to complete them. All of the tasks are performed in a seated position at a table and evaluated using an easy-to-use measure, the TCT. The seated position only allows for limited assessment of issues arising from the limb position effect. Furthermore, the SHAP is comprised of unilateral tasks, which are all based on grasping actions.

A good example of a test targeted at multi-articulated prostheses and complex tasks is the CRT. This test requires simultaneous activation of a prosthetic wrist and hand. As the name suggests, clothespins need to be relocated from a horizontal bar to a vertical one, which, in this case, requires a rotation of the clothespins while maintaining a firm grip. Since the CRT consists of one task only, it offers rather little variability in its execution. Furthermore, only once a user is proficient in the use of their prosthesis can the CRT offer insight into the user's capabilities. Additionally, assessing a single task may offer only a little information about a user's capabilities in daily living tasks.

Finally, a common and easy-to-administer tool for hand functionality assessment is the BBT. The setup of this test consists of two compartments separated by a divider.

Multiple 25mm blocks are placed in one compartment, and the goal of the test is to transfer as many blocks as possible from one compartment to the other within a certain amount of time. Versions of this test have been implemented in VR [v]. The BBT has a drawback, which relates to the random arrangement of the blocks to transfer. Potentially, the arrangement can be such that blocks are located directly next to each other, forming an almost closed surface, which makes grasping them challenging. To avoid issues of that sort, a modified BBT was developed with a specific arrangement of blocks [229].

These tools are established clinical tests that provide, to a large extent, objective measures of performance. They address a number of essential characteristics of a multi-articulated prosthesis with ML-based myocontrol, such as repeatability and appropriate difficulty, tasks based on ADLs involving multiple actions, tasks requiring different body poses and an easy-to-use objective assessment measure. None of the aforementioned tests combines all of these points. However, the ARM competition of the Cybathlon covers the aforementioned aspects quite well and can provide benchmark measurements. Due to its strong competitive nature and focus on retraining the same tasks to improve the performance speed, it makes its application as an assessment and training tool difficult.

We addressed the necessity for such a tool in Publication 4 by developing and testing the SATMC, an assessment tool designed for modern prostheses using an ML-based myocontroller. It combines assessment with user training in a multi-session protocol that supports training at a user-specific level of difficulty while using simple measures to assess performance.

3 Summary of Publications

This chapter contains summaries of all publications that contributed to this thesis. For each publication, we provide the *authors*, the *medium of publication*, the *abstract*, the *contribution of the thesis author* based on CRediT [230], and information regarding *copyright*.

Publication 1 Action Interference in Simultaneous and Proportional Myocontrol: Comparing Force- and Electromyography

Authors Markus Nowak, Thomas Eiband, Eduardo Ruiz Ramírez, and Claudio Castellini

Journal Journal of Neural Engineering

Abstract Myocontrol, that is, control of a prosthesis via muscle signals, is still a surprisingly hard problem. Recent research indicates that surface electromyography (sEMG), the traditional technique used to detect a subject's intent, could proficiently be replaced, or conjoined with, other techniques (multi-modal myocontrol), with the aim to improve both on dexterity and reliability. In this paper we present an online assessment of multi-modal sEMG and force myography (FMG) targeted at hand and wrist myocontrol. Twenty sEMG and FMG sensors in total were used to enforce simultaneous and proportional control of hand opening/closing, wrist pronation/supination and wrist flexion/extension of 12 intact subjects. We found that FMG yields in general a better performance than sEMG, and that the main drawback of the sEMG array we used is not the inability to perform a desired action, but rather *action interference*, that is, the undesired concurrent activation of another action. FMG, on the other hand, causes less interference.

Contribution of the thesis author Data curation, Formal Analysis, Methodology, Software, Supervision, Validation, Visualization, Writing — original draft, Writing — review & editing

Publication 2 Simultaneous and Proportional Real-Time Myocontrol of up to Three Degrees of Freedom of the Wrist and Hand

Authors Markus Nowak, Ivan Vujaklija, Agnes Sturma, Claudio Castellini, and Dario Farina

Journal IEEE Transactions on Biomedical Engineering

Abstract Achieving robust, intuitive, simultaneous and proportional control over multiple degrees of freedom (DOFs) is an outstanding challenge in the development of myoelectric prosthetic systems. Since the priority in myoelectric prosthesis solutions is robustness and stability, their number of functions is usually limited.
Objective: Here, we introduce a system for intuitive concurrent hand and wrist control, based on a robust feature-extraction protocol and machine-learning.
Methods: Using the mean absolute value of high-density EMG, we train a ridge-regressor (RR) on only the sustained portions of the single-DOF contractions and leverage the regressor's inherent ability to provide simultaneous multi-DOF estimates. In this way, we robustly capture the amplitude information of the inputs while harnessing the power of the RR to extrapolate otherwise noisy and often overfitted estimations of dynamic portions of movements.
Results: The real-time evaluation of the system on 13 able-bodied participants and an amputee shows that almost all single-DOF tasks could be reached (96% success rate), while at the same time users were able to complete most of the two-DOF (62%) and even some of the very challenging three-DOF tasks (37%). To further investigate the translational potential of the approach, we reduced the original 192-channel setup to a 16-channel one and the observed performance did not deteriorate. The amputee performed similarly well to the other participants, according to all considered metrics.
Conclusion: This is the first real-time operated myocontrol system that consistently provides intuitive simultaneous and proportional control over 3-DOFs of wrist and hand, relying on only surface EMG signals from the forearm.
Significance: Focusing on reduced complexity, a real-time test and the inclusion of an amputee in the study demonstrate the translational potential of the control system for future applications in prosthetic control.

Contribution of the thesis author Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing — original draft, Writing — review & editing

Publication 3 Applying Radical Constructivism to Machine Learning: A Pilot Study in Assistive Robotics

Authors Markus Nowak, Claudio Castellini, and Carlo Massironi

Journal Constructivist Foundations

Abstract **Context** In this article we match machine learning (ML) and interactive machine learning (iML) with radical constructivism (RC) to build a tentative radical constructivist framework for iML; we then present a pilot study in which RC-framed iML is applied to assistive robotics, namely upper-limb prosthetics (myocontrol).
Problem Despite more than 40 years of academic research, myocontrol is still unsolved, with rejection rates of up to 75%. This is mainly due to its unreliability — the inability to correctly predict the patient's intent in daily life.
Method We propose a description of the typical problems posed by ML-based myocontrol through the lingo of RC, highlighting the advantages of such a modelisation. We abstract some aspects of RC and project them onto the concepts of ML, to make it evolve into the concept of RC-framed iML.
Results Such a projection leads to the design and development of a myocontrol system based upon RC-framed iML, used to foster the co-adaptation of human and prosthesis. The iML-based myocontrol system is then compared to a traditional ML-based one in a pilot study involving human participants in a goal-reaching task mimicking the control of a prosthetic hand and wrist.
Implications We argue that the usage of RC-framed iML in myocontrol could be of great help to the community of assistive robotics, and that the constructivist perspective can lead to principled design of the system itself, as well as of the training/calibration/co-adaptation procedure.
Constructivist content Ernst von Glasersfeld's RC is the leading principle pushing for the usage of RC-framed iML; it also provides guidelines for the design of the system, the human/machine interface, the experiments and the experimental setups.

Contribution of the thesis author Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing — review & editing

Publication 4 Simultaneous Assessment and Training of an Upper-Limb Amputee using Incremental Machine-Learning-based Myocontrol: A Single-Case Experimental Design

Authors Markus Nowak, Raoul M. Bongers, Corry K. van der Sluis, Alin Albu-Schäffer, and Claudio Castellini

Journal Journal of NeuroEngineering and Rehabilitation

Abstract **Background** Machine-learning-based myocontrol of prosthetic devices suffers from a high rate of abandonment due to dissatisfaction with the training procedure and with the reliability of day-to-day control. Incremental myocontrol is a promising approach as it allows on-demand updating of the system, thus enforcing continuous interaction with the user. Nevertheless, a long-term study assessing the efficacy of incremental myocontrol is still missing, partially due to the lack of an adequate tool to do so. In this work we close this gap and report about a person with upper-limb absence who learned to control a dexterous hand prosthesis using incremental myocontrol through a novel functional assessment protocol called SATMC.
Methods The participant was fitted with a custom-made prosthetic setup with a controller based on *Ridge Regression with Random Fourier Features* (RR-RFF), a non-linear, incremental machine learning method, used to build and progressively update the myocontrol system. During a 13-month user study, the participant performed increasingly complex daily-living tasks, requiring fine bimanual coordination and manipulation with a multi-fingered hand prosthesis, in a realistic laboratory setup. The SATMC was used both to compose the tasks and continually assess the participant's progress. Patient satisfaction was measured using Visual Analog Scales.
Results Over the course of the study, the participant progressively improved his performance both objectively, e.g., the time required to complete each task became shorter, and subjectively, meaning that his satisfaction improved. The SATMC actively supported the improvement of the participant by progressively increasing the difficulty of the tasks in a structured way. In combination with the incremental RR-RFF allowing for small adjustments when required, the participant was capable of reliably using four actions of the prosthetic hand to perform all required tasks at the end of the study.
Conclusions Incremental myocontrol enabled an upper-limb amputee to reliably control a dexterous hand prosthesis while providing a subjectively satisfactory experience. SATMC can be an effective tool to this aim.

Contribution of the thesis author Conceptualisation, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualisation, Writing — original draft, Writing — review & editing

4 Discussion

In the context of this work, we approached the improvements of myocontrol for upper-limb prosthetics from different angles. As outlined in Section 1.4, these involve advancements in the areas of **muscle signals**, **theory on user-prosthesis interaction** and **simultaneous assessment and training**.

We could successfully show that FMG contains additional information for myocontrol compared to EMG, that interaction is key in controlling prosthetics devices, that a transparent and robust myocontroller can be intuitively used and that structured assessing and training leads to successful and satisfying usage of ML-based prostheses. We were able to show improvements regarding **limb position effect**, **contraction intensity effect**, **within/between day effect**, and **extensive training in ML-based myocontrol**. These areas are considered current challenges in ML-based myocontrol. The investigations that led to these conclusions concentrated on putting the user in the focus, providing high significance to the impact of our results. This was achieved through fostering co-adaptation by using interactive ML approaches.

4.1 User Adaptation

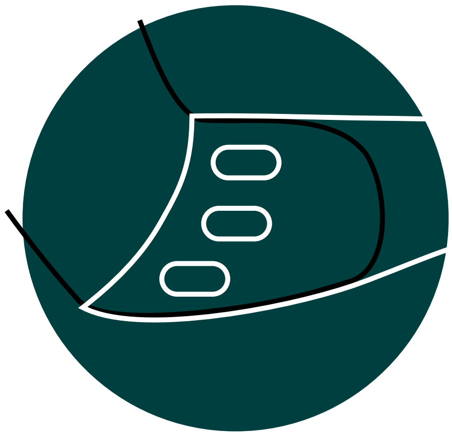


Figure 4.1: Area of user and prosthesis interaction: ● muscle signals

Closing the loop by providing feedback to the user allows for user adaptation. Avoiding this pathway by drawing conclusions about myocontrol purely from data-driven studies has led to issues in the conversion of scientific findings to novel prosthetic developments [20, 133, 152, 214, 215, 216]. For this reason, all the studies this thesis is based upon are online user studies with real-time visual feedback to the user. The studies performed for Publication 1, Publication 2 and Publication 3 involved goal-reaching tasks in an on-screen environment. The long-term user study for Publication 4 went one step further and included tasks based on ADLs and a custom-built prosthetic provision.

Two studies were specifically concerned with the adaptation of the user, Publication 3 and Publication 4. In Publication 1 and Publication 2, no adaptation on the side of the ML-based myocontroller was used. In these studies, we provided the user with improved myocontrollers and investigated their capability to adapt and apply the control algorithm.

Fusion

One of the aforementioned improvements was the addition of FMG to an sEMG-based myocontroller. Fusion of these sensor modalities aimed at providing the user with a more robust and stable myocontroller.

The study covered a comparison between three different sensor-modality configurations. These are only using sEMG sensors, only using FMG sensors, and a fusion of the two sensor types. For fusion, we investigated two approaches, one fusing the two sensor modalities on the feature level and an ensemble approach [231]. User adaptation was investigated in an online user study involving 12 people without limb absence by reaching targets that were not explicitly trained. The users trained the myocontroller with three DOFs, hand open/close, wrist pronation/supination and wrist flexion/extension at a comfortable level of force. These were labelled with full activation of the associated DOF (1.0), and subsequently, the users were asked to reach targets at different levels of activation, i.e. 0.33, 0.67 and 1.0. The choice of goals allowed us to investigate the **contraction intensity effect**. Figure 4.2 presents a visualisation of this process. To our understanding, this was the first online user study with a myocontroller based on the fusion of sEMG and FMG.

In this study, we were able to show that FMG is a promising extension of sEMG. As the FMG-only modality led to a similar performance as the fused approach and to an improved one compared to the sEMG-only modality, it could even be seen as a potential alternative. These online results confirm the offline findings of other studies [89, 96, 97, 232]. Ahmadizadeh et al. [89] have equipped a prosthetic socket with 37 FMG sensors and two sEMG sensors. In an offline comparison, the conclusion was drawn that the addition of sEMG does not lead to a significant improvement. As the number of sensors per modality is highly unbalanced, a potential unwanted influence could have been the higher number of FMG sensors. Hence, we have put particular effort into balancing the sensor numbers in Publication 1. We used 20 sensors in total: ten FMG sensors and ten sEMG sensors. For individual-modality myocontrol, ten sensors of the same type were used, while in the fused approach, five of each modality were combined. An alternating arrangement on two bracelets with a one-electrode offset between the bracelets allowed measuring approximately the same underlying structure with both modalities. Eventually, the results of the balanced case matched the unbalanced one. However, promising findings have been made with co-located fused sensors [181]. With

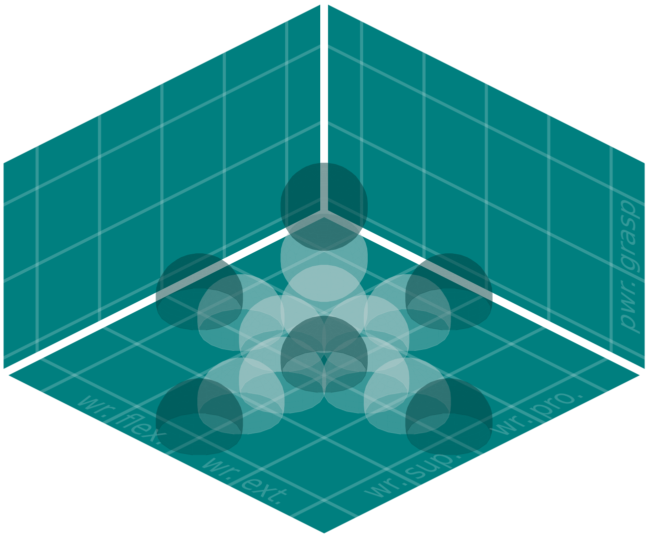


Figure 4.2: Visualisation of training and testing data for the goal-reaching tasks of the user study in Publication 1. Training actions in ●, and testing actions in ●. Training actions were among the testing actions

this type of sensor, the fusion of FMG and sEMG provides significantly better offline results.

Furthermore, we were able to identify a promising feature of FMG related to user adaptation, which directly concerns the **contraction intensity effect**. Based on our training and testing approach, users were asked to reach goals at untrained lower levels of activation intensity. While we were not able to find online differences in the performance at the trained full activation level, the adaptation and fine control at lower levels of activation intensity were significantly better with FMG than with sEMG. We were able to show that the difference in performance originated from action interference at these low levels of activation for sEMG, potentially the origin of the **contraction intensity effect**. Ke et al. [180] came to a very similar conclusion in their study about a novel sEMGFMG sensor. They showed that at low levels of muscular activity, FMG signals are more prominent than sEMG signals.

In our study, we were able to show that FMG provides highly promising features that can support user adaptation by reducing the impact of the **contraction intensity effect**. By doing so, a more stable, robust, and potentially more intuitive myocontroller could be realised.

Transparent Control

User adaptation is not only a beneficial feature when dealing with different activation levels of an action but can also be extended to the combination of multiple DOFs. Under the keyword transparent control, we investigated the capability of a user to control multiple DOFs at different levels of intensity as well as in combined actions. Such a myocontroller is an instance of SPC. A number of SPC approaches have been investigated, either using extended classification [133, 134, 135, 136] or regression algorithms [132, 140, 141, 143, 144].

To achieve SPC, the majority of studies require training data of combined actions and continuously labelled data. When more than two DOFs are controlled, gathering training data becomes extensive, with an exponentially growing number of combinations and potential difficulties executing these combined actions [104, c, 165]. Furthermore, continuously labelled data requires contra-lateral labelling, following a visual stimulus or similar measures, which can potentially lead to wrongly labelled data due to delays or difficulty in mirror movement performance [144].

In order to design a realistic myocontroller, we relied on user adaptation rather than extensive ML training. Hence, in the study for Publication 2, the users train only on the full activation of an action and no training on combined actions was required due to a linear design of the myocontroller. This myocontroller effectively reduced **extensive training in ML-based myocontrol** and dealt with the **contraction intensity effect**, two major challenges in myocontrol described in Section 1.3.

We chose to use a simple and linear ML approach, namely RR. For a near-to-linear relation between measured sEMG and control output, the only sEMG feature extracted was its envelope calculated using the RMS [132]. To ensure that we gathered as much muscular information as possible, we used HD-sEMG. Investigations have shown that choosing the appropriate feature set can make the intent detection problem essentially linear [115, 233]. Furthermore, with an appropriate feature set, linear and non-linear regression methods perform comparably [144]. Based on these findings, we designed a myocontroller using HD-sEMG, the RMS, and RR that puts the focus on the capabilities of the user rather than on controller complexity. A user study with 13 people without limb absence and one person with limb absence was designed using goals that take physiological considerations of combined DOFs into account, as mentioned in Section 2.3.2. Figure 4.3 depicts the training and online testing data to visualise the capability of the user and myocontroller to generalise to unseen data.

The aim of transparent control is to provide an easy-to-use interface for the user. Transparency in this work refers to the property of a controller, which allows the user to easily anticipate the outcome. With this property, the potential shortcomings of a controller can be compensated by the ability of the user to adapt.

With this transparent controller, we were able to demonstrate SPC of three DOFs by only training on individual DOFs at one single level of activation. A result that directly affects **extensive training in ML-based myocontrol** and the **contraction intensity effect**. It has to be noted that the performance drops significantly with an increasing number of DOFs. However, the capability to reach goals involving simultaneous activation of up to three DOFs does not come at the expanse of single-DOF control. Such a controller has been successfully implemented and tested for two DOFs [153]. Other studies report three- and even four-DOFs SPC based on muscle signals [221, 234, 235]. However, some differences have to be highlighted. Although simultaneous activation is possible, eventually, it is not required to reach multi-DOF goals due to the type of controller used. These studies utilise velocity control, which allows sequential

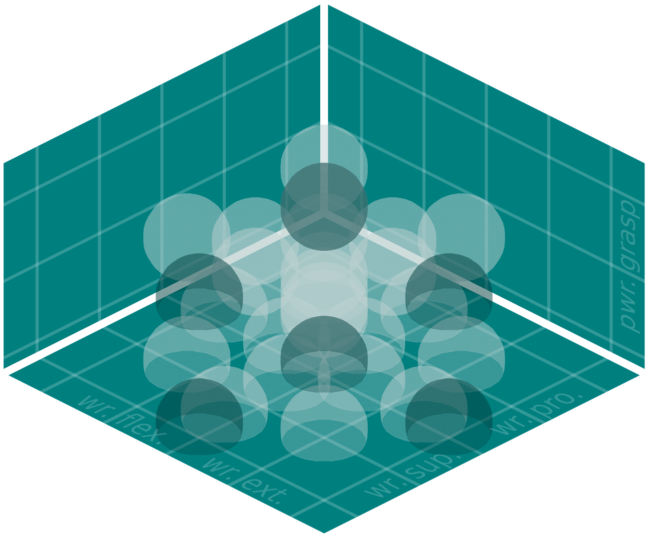


Figure 4.3: Visualisation of training and testing data for the goal-reaching tasks of the user study in Publication 2. Untrained combined actions were among the test tasks. Training actions in ●, and testing actions in ●. The training action for power grasp was among the testing actions

activation of individual DOFs to reach multi-DOF targets. Ortiz-Catalan et al. [221] have shown consistent SR of approx. 90% for single- and multi-DOF targets. However, in addition to velocity control, the ML algorithm was trained with multi-DOF actions. This simplifies the intent detection considerably, and the authors do not mention to what extent simultaneous activation of DOFs contributed to reaching multi-DOF goals. On the other hand, Smith et al. [235] were able to quantify this value and reported that the maximal two-DOF activation occurred in two-DOF tasks with $48.7\% \pm 1.7\%$ of the task duration and respectively $26.4\% \pm 3.0\%$ for three-DOF activation in three-DOF tasks. Their myocontrol algorithm was trained with multi-DOF activations and predicted the velocity per DOF, as well. Ison et al. [234] used an NMF-based regression framework to control the velocity along four DOFs. No SR in the virtual or robotic tasks was reported since the tasks were evaluated based on the time they took, not whether they could be accomplished within a specific time frame. Furthermore, there was no mention of the amount of simultaneous activations that were used during task execution. An interesting similarity stems from the sparsity of the NMF method. In our study, we have performed a sensor-reduction analysis to successfully show the robustness and translational potential of the developed myocontroller to a prosthetic setup. The NMF-based controller by Ison et al. identified areas of high information content and, due to sparsity, effectively performed a sensor reduction. These findings agree with what has been found in the literature regarding sensor reduction [139, 236, 237].

Outside of wrist and hand actions, Barsotti et al. [238] have performed a similar study concerned with the combination of single-finger actions. Their training and testing protocol is, to a large extent, consistent with ours, with the exception that a trapezoidal stimulus was used instead of steady-state training. Furthermore, their myocontrol was also based on 192 EMG sensors and a RR myocontroller with a slightly different EMG feature, i.e. linear envelope instead of an RMS envelope. The resulting performance was similar to our study but at a lower level, with an SR for single-DOF tasks of $85\% \pm 9\%$ compared to $96\% \pm 2\%$, 40% compared to $55\% \pm 5\%$ for two-DOF tasks and 18% compared to $37\% \pm 7\%$ for three-DOF tasks. The main objective of said study was the comparison between a linear feature and a non-linear one. The non-linear feature led to a considerably better performance, with an SR for double-DOF tasks of 67% and 33% for three-DOF tasks. These values agree to a large extent with our findings. Since the non-linear feature was based on physiological considerations, it potentially could compensate for non-linearities in multi-finger actions that were not present in combined wrist and hand actions in our study.

Other approaches to SPC for multiple DOFs have been investigated. Amsüss et al. [160] have combined a classification approach for single-DOF actions with a regression-based approach for multi-DOF actions. Based on a dimensionality estimator, a continuous transition was possible between the prediction of the single-DOF classifier and the multi-DOF regressor. ML training required three trapezoidal data acquisitions at three different levels of activation, and the regressor was only able to predict the combination of two DOFs. The results obtained in Publication 2 suggest that the classifier might not be required as the SR for single-DOF tasks was at $96\% \pm 2\%$. However, the authors were able to show significant improvement over a classical sequential myocontrol in functional tests (SHAP and BBT).

4.2 Adaptation in Machine Learning

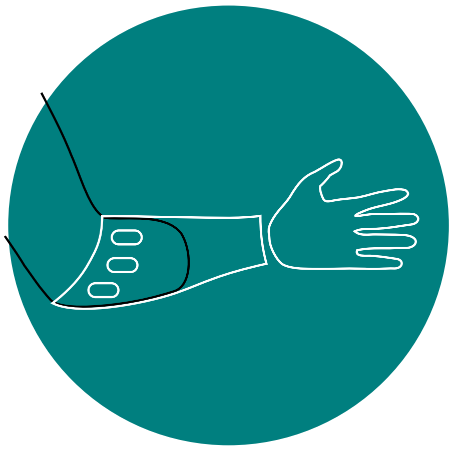


Figure 4.4: Area of user and prosthesis interaction: ● theory on user-prosthesis interaction

In order to fully make use of co-adaptation in myocontrol, the ability of the user to adapt has to be accompanied by an adaptive myocontrol algorithm. This requires an ML method that allows for interaction, such as iML approaches. As the user adapts and learns the signals they produce likely change. This novel information should be presented to the myocontroller so it can update its model while potentially discarding obsolete information. iML methods have mechanisms for both of these scenarios: updates and forgetting [c, 164]. In case it is not mathematically possible for a myocontrol algorithm to be updated incrementally, a simplified definition of incrementality can be applied. Given enough memory and enough computational power to perform sufficiently fast training, a reevaluation of the training data after the addition of novel and/or removal of obsolete data can be considered. This simplified definition has been applied in Publication 4, where the reevaluation of the training data lasted only a few seconds.

Adaptive approaches have found appeal in myocontrol. They have been used for different purposes in ML-based myocontrol. Figure 4.5 depicts four different approaches in that area that are characterised by interactive or non-interactive training and interactive or non-interactive testing.

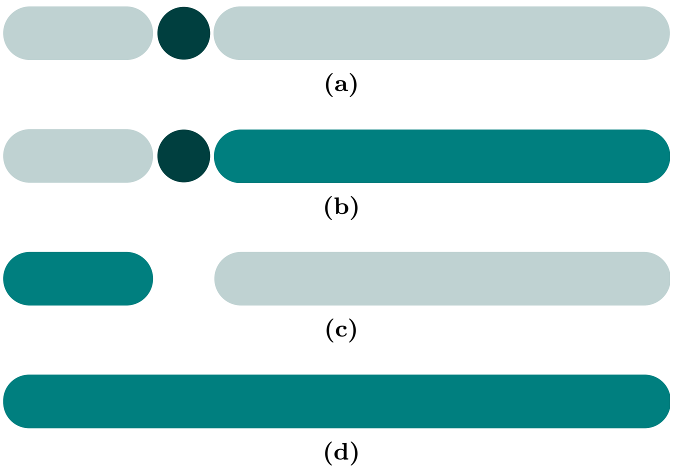


Figure 4.5: Different types of ML adaptation in myocontrol. represents non-interactive training or testing, represents interactive training or testing, and represents a dedicated model training phase. From left to right, the chronological process of ML training and testing is visualised with training data acquisition, dedicated model training and model testing. (a) non-interactive training, model training, and non-interactive testing; (b) non-interactive training, model training, and interactive testing; (c) interactive training, and non-interactive testing; (d) interactive training and testing

One application of adaptive approaches aims to deal with non-stationary changes due to donning and doffing, sweating, fatigue or electrode shift [239, 240, 241]. These algorithms are usually based on supervised updates or updates with high-confidence data. It has been shown that an adaptive approach for this purpose leads to better performance compared to non-adaptive ones [242, 239, 240]. A study of our own has come to the same conclusion [c]. As these approaches are characterised by updates during online usage, they correspond to the ones in Figure 4.5b and Figure 4.5d. Sensinger et al. [242] have investigated multiple supervised and unsupervised adaptation approaches and have found that a larger error reduction is possible with supervised methods compared to unsupervised ones.

Another area in myocontrol where adaptive algorithms have been applied is during data acquisition for ML training [165, 166, 243]. The training phase of these approaches includes not only a supervised data acquisition but also a testing phase of the preliminary model. A set of goal-reaching tasks are performed based on the initial data collection. In case a target can not be reached, the ML algorithms adapt to make said target reachable. After this adaptive training phase, the following usage of the model usually does not involve interaction possibilities. A visualisation of this approach can be found in Figure 4.5c.

The supervised interaction investigated in Publication 3 can be considered another type of adaptation in myocontrol. The variants described before involve automatic supervised updates with data that has a high likelihood of being correctly labelled. However, there are a number of situations where an ML algorithm fails because of unknown data or data with low certainty. In these situations, the user performs an action, and the algorithm can not interpret the data correctly. However, since the user is aware of the correct action, a triggered update in these situations can be labelled correctly and provide highly relevant data to the ML algorithm.

This interaction step between the user and the ML algorithm is not present in the adaptive approaches described before and, in our opinion, is key to establishing a successful myocontroller. The interaction-based mechanism has been described in Publication 3 from an RC point of view.

In this study, we investigated three different levels of interaction between the user and the ML algorithm. These were non-interactive training and non-interactive testing, interactive training and non-interactive testing and a single phase of interactive training and testing, which can be found in Figure 4.5a, Figure 4.5c, and Figure 4.5d, respectively. We were able to show the benefits of interaction between the user and ML algorithm. Although not significant, the error (normalised RMSE) was lowest for the interactive approach. The judgement of the user, however, was significant, with significantly more "good" evaluations in the interactive case than in the other two.

Furthermore, we could show that the person providing the signals can assess correctly whether the prosthesis performs appropriately or not. Although this finding appears obvious, the implications are highly relevant. Being able to correctly evaluate the performance of the prosthesis further underlines the necessity of interaction between the user and the prosthesis in prosthetic control. Given an incremental myocontroller and the theoretical capability of the said algorithm to find an appropriate model, the RC framework can push myocontrol to become truly robust in daily living.

In order to reduce the duration of the experiment for the individual user, the study was designed between-subject instead of within-subject. This led to the unfortunate situation where two subjects had to be excluded from the study since their performance was considered to be outliers. In order to have a balanced comparison, four instead of the originally planned five participants per category were included in the statistical analysis. The result of the ANOVA ($F(2, 9) = 3.96, p = 0.058$) gives room to the conclusion that an effect could have been found with a higher number of participants.

Furthermore, we would like to highlight that there might be another interesting phenomenon that could be exploited for interaction. In the non-interactive part, a participant expressed they felt “the machine was learning”. In fact, the trained model did not change, and if there was improvement, it originated from the participant learning. Due to the change in perspective in the RC framework, the participant is already capable of performing every action; only the prosthesis has not understood it yet. This might remove some pressure from the users as, in their perception, it’s the prosthesis that has to learn rather than them. As mentioned in Section 1.3, **extensive training in ML-based myocontrol** is among the current challenges in myocontrol and reduced burden through interaction would directly affect this issue. Changing the framing of this process is a promising approach to reducing abandonment. The importance of this approach can be further underlined by the personal experience of the author in the user study performed for Publication 2. A person with limb absence involved in said study expressed during the preparation process for their participation that they simply could not perform one of the actions required for the study. There was no possibility of even attempting to perform that action since they insisted they were not capable of doing so. While this statement can very well be true, a different approach through the RC framing could have made a difference. The point of view where they are already able to perform that action, the prosthesis just hasn’t learnt it yet, might have unlocked hidden capabilities they were not aware of.

These ideas have found footing in the community and may shape the next developments in user-prosthesis interaction [244]. Based on these ideas, we designed an automated oracle with the goal to support the user in identifying situations of uncertainty and, therefore, opportunities to update the system [o, r, u]. The oracle monitors the stability of the prosthetic provision by explicitly taking information from the prosthetic hardware into account. We were able to show that this additional source of information leads to more informed decisions on the stability of the prosthetic performance.

4.3 Co-Adaptation in Practice

Having shown the benefits of adaptation on the side of the user and the ML algorithm now requires the demonstration of improvements due to co-adaptation in myocontrol. To do so, one needs an appropriate test that considers all relevant aspects [224].

This test should include the assessment of interaction and should be tailored to multi-articulated prostheses capable of multiple actions. Furthermore, multiple sessions or retests are required since interaction particularly leads to improvement when learning or, in general, changes are involved. Due to potential improvements, one single task or one single level of difficulty is not sufficient, and a modality to involve increasing difficulty is required. Based on these ideas, we defined four essential aspects for such a test: repeatability and increasing difficulty (A1), postural variation during tasks (A2), multiple actions per task (A3), and a short familiarisation time for the rater (A4). Furthermore, these four aspects allow us to assess a number of current challenges in

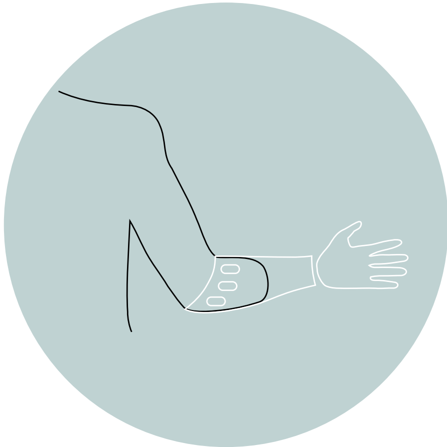


Figure 4.6: Area of user and prosthesis interaction: ● simultaneous assessment and training

myocontrol, such as **limb position effect**, **within/between day effect** and **extensive training in ML-based myocontrol**.

On the basis of the essential aspects (A1-A4), we have compared different functional tests to find a suitable candidate. A description of a number of functional tests has been provided in Section 2.5.2. The comparison between ACMC, SHAP, CRT and BBT showed that none of these tests is capable of fully assessing interaction using iML methods for myocontrol, and only the CRT is capable of assessing multi-articulated prostheses. Needs for a standardised assessment framework have been voiced in the community [115, 245].

Therefore, we designed the SATMC, an assessment protocol that could deal with all the aforementioned aspects (A1-A4) and which, at the same time, serves as a training tool based on incremental updates, see Publication 4. Using the SATMC, we performed a user study involving a person with limb absence that was fitted with a custom-built socket and a multi-articulated prosthetic hand controlled by the iML-based algorithm introduced in Section 2.3.4. From being completely new to ML-based myocontrol, the user learned to control four DOFs of the prosthetic hand reliably. A protocol and user study that lasted more than 30 sessions over 13 months, that was based on an objective increase in complexity of tasks, and that involved an iML-based myocontrol has, to the best of our knowledge, not been performed prior to this work.

However, there are a number of studies that have dealt with user training for ML-based myocontrol. Atkins and Sturma [246] have provided a hands-on overview regarding the testing and training of myoelectric prosthetic hands. Usually, the first step in preparation for myoelectric control is pure signal training [169]. In this early period, the number of actions, as well as the different EMG-signal patterns, are identified. As the first months of rehabilitation are essential for acceptance of a prosthesis, early training with the prosthesis, as promoted by the SATMC, can be beneficial. A comparable interactive training has been successfully shown by Simon et al. [247]. Instead of incremental updates, full retraining was performed for each update. However, in this home trial, the retraining could be triggered by the users themselves. Already with this interaction possibility, ML-based control showed better outcome measures than direct control [167]. The SATMC could provide further improvements since an initial evaluation of the capabilities and the number of DOFs to control preceded these home trials [248].

Roche et al. [249] have developed a training protocol for multi-articulated prosthetic control that builds on ideas similar to ours. The goal is to support the user in reaching more dexterity, i.e., learning more actions. Through a process involving imitation, repetition, and reinforcement, they were able to show the efficacy involving one person with limb absence. The approach does not feature an incremental increase in controller complexity nor an increase in the difficulty of the tasks. Imitation of the movement of a real hand appears to have played a central role in this protocol [250].

Resnik et al. [169] have performed a multi-session experiment to compare direct control and ML-based control. No clear conclusion could be drawn since both control modalities performed similarly in the assessment tasks. The ML-based control involved two DOFs, and taking this into account, we have found similar results in our study. The user in our study performed a single session of the SATMC with his own prosthesis with direct control. At that time of the study, the user was capable of controlling two actions (and a rest gesture). Timing and self-assessment were on a similar level as the ML-based controller. When increasing the number of DOFs to control to three, ML-based control performs better than direct control [251]. We were not able to recreate this comparison directly. However, for three-DOF control (and a rest gesture), satisfaction and timing reached levels similar to those of the session with direct control, which could indicate higher dexterity while maintaining a stable control behaviour.

The study by Resnik et al., as well as a number of similar ones [252, 253], have performed multi-session user studies involving at least one person with limb absence. Although the number of participants is low, these studies have the potential to provide strong evidence of their results. Using the concept of SCED can improve user studies in myocontrol, where getting access to prosthetic provisions custom-built for an investigation can be challenging. In Publication 4, we applied SCED, used direct replication, and a consistent baseline measure to strengthen our findings.

4.4 Limitations

Although the investigations performed in this thesis led to a number of promising results, they are not without limitations. In short, these are:

- The potential impact of the **limb position effect** on the sEMG-FMG-fusion study in Publication 1 and on the transparent control study in Publication 2 was not investigated.
- The results in the interaction study in Publication 3 only weakly show the improvement interaction offers to myocontrol.
- The cohort of participants in the studies in Publication 1 and Publication 3 consisted only of people without limb absence.

- Physiologically inspired approaches could be an alternative to interaction to deal with the instabilities of ML-based myocontroller.

For one, the study regarding sEMG and FMG fusion could be impacted by the **limb position effect**. The participants were seated at a table and were asked to rest their elbows on the table. With an elbow angle of approximately 90°, the forearm and hand were almost vertically pointing towards the ceiling. Figure 1 in Publication 1 shows a participant during the user study. The participants were asked to perform the entire user study in said position. This was the only pose where the comparison between fusion methods was performed. Radmand et al. [88] have investigated the impact of the limb position effect on a myocontroller based on high-density FMG (TMG). They have found that training the myocontroller in multiple positions can reduce the classification error from around 10% to around 2% in ADLs. Ahmadizadeh et al. [89] have used a dynamic training approach to include different limb positions in the training data. Since our online findings matched their offline analysis, the influence of the **limb position effect** could, therefore, be low. An online user study with tasks requiring different limb positions that tests different fusion approaches with a balanced sensor number should provide a more realistic scenario and, therefore, a better indication of the benefits of the fusion of sEMG and FMG. Since the data acquisition setup used in Publication 1 is portable, the extension to investigate the limb position effect is feasible. In the study regarding transparent control published in Publication 2, the same considerations regarding the limb position apply since the restrictions to the pose of the arm were essentially the same. However, the setup of that study can not easily be used in a portable manner. Alternative mobile HD-sEMG acquisition devices exist, such as the *MuoviPro* [254] or *Muovi+Pro* [255] by *OT Bioelettronica s.r.l.*.

Furthermore, the results obtained in the interaction study of Publication 3 do not show significant improvement in normalised RMSE when increasing the interaction level. However, the effect could have been too weak to be shown with four participants per condition. It was required to remove one participant per category (moving from five participants to four) since their performance was considered to be outliers, which could lead to a false bias in the between-subject design of the study. A repetition or extension of the experiment with a larger number of participants could lead to stronger results.

Additionally, a limitation in the aforementioned fusion study and interaction study in Publication 1 and Publication 3, respectively, concerns the lack of people with limb absence. Investigations in a cohort of people without limb absence can be a valuable source to identify promising avenues that are worth investigating with prosthetic setups and people with limb absence. The fusion study of Publication 1 was, to the best of our knowledge, the first online comparison of sEMG and FMG fusion approaches. Investigations regarding said sensor fusion have been performed with people with limb absence as participants; however, only offline. In Ahmadizadeh et al. [89], a prosthetic socket equipped with 37 FMG and two sEMG sensors was used to assess sensor fusion approaches with a person with limb absence. Our online results confirmed their findings that the addition of sEMG does not significantly improve the FMG-only myocontroller. This indicates that our findings with people without limb absence could transfer to people with limb absence. However, a dedicated user study is still required. Regarding the interaction study of Publication 3, the involvement of people with limb absence would provide highly valuable insights. The findings of the initial study could be extended by an investigation of whether there is a transfer of findings from people without limb absence to people with limb absence. This is particularly interesting since it has been shown that prosthesis users embody a prosthesis neither as a tool nor as a hand but rather as a category of its own [207]. This could potentially have a relevant effect on the changed perspective the RC framework provides.

Finally, interaction is not the only approach to deal with instabilities in ML-based myocontrol. Alternative concepts aim at resolving this issue through physiologically inspired approaches [256, 257, 258]. These can rely on musculoskeletal models, such as the upper-limb model by Holzbaur et al. [259] or Saul et al. [260], which can be used with *OpenSim* [261], a simulation environment where muscles are simulated using a Hill-type model [262]. Further simulation environments exist, e.g. the *AnyBody Modeling System* [263]. Model-based approaches can also be based on the composition of the EMG signal. They involve EMG decomposition to extract the neural drive, see Section 2.2.1. Real-time implementations of these decomposition algorithms have been developed in recent years [264, 265, 266]. With a deeper understanding of the underlying generation of neural control, such as the newly developed concept of synergistic activation of MUs [68], the ambitious goal of decomposing the entire motor control of the central nervous system is drawing nearer, which could make supervised ML-based myocontrol obsolete.

5 Conclusion

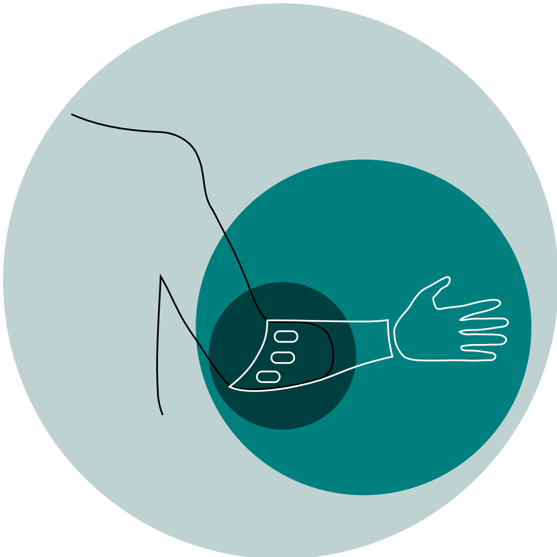


Figure 5.1: Different areas of user and prosthesis interaction addressed in this thesis. ● muscle signals; ● theory on user-prosthesis interaction; ● simultaneous assessment and training

In the studies performed in this thesis, we were able to show the improvements that interaction can bring to myocontrol and how co-adaptation can be a solution to the current challenges in myocontrol.

We addressed each challenge related to ML-based myocontrol that was introduced in Section 1.3. Interactive incremental updates proved to be a successful modality to deal with the **limb position effect** in the user study in Publication 4. Investigating the benefits of different sensor modalities, such as the fusion of FMG and sEMG, in the user study in Publication 1 showed the reduced susceptibility of FMG signals to the **contraction intensity effect**. Furthermore, the user study in Publication 2 showed the positive aspects of adaptation of the user on the **contraction intensity effect** and on **extensive training in ML-based myocontrol**. With a transparent ML approach and minimal training, the users were capable of navigating the full action space using SPC. Since interaction through incremental updates directly impacts **extensive training in ML-based myocontrol**, the user studies in Publication 3 and Publication 4 provide evidence of reducing the negative aspects of this effect. Regarding the **within/between day effect**, the multi-session user study in Publication 4 showed that only occasional updates are required once a satisfactory level of control is reached. This has been evident in the said study due to a number of consecutive sessions with a high-performance level and no model updates.

We have successfully addressed the aforementioned challenges by exploiting the ability of the user to adapt through interaction using iML-based myocontrol. Our investigations in different areas of user and prosthesis interaction — **muscle signals**, **theory on user-prosthesis interaction** and **simultaneous assessment and training** — depicted in Figure 5.1 demonstrate that co-adaptation in upper-limb prosthetics is a promising avenue to improving the user experience.

5.1 Future Work

Based on the work in this thesis, its limitations and existing literature, a number of perspectives for future investigations can be identified. In short, these can involve:

- Extending our user studies regarding FMG and sEMG fusion and transparent control by tasks involving different limb poses to assess the **limb position effect**.
- Performing a user study based on the SATMC with a multi-modal and transparent myocontroller.
- Investigating different features regarding their potential for transparent control.
- Extending co-adaptive training with unsupervised methods to further emphasise the capabilities of the user.
- Automating the SATMC to reduce experimenter errors.
- Transfer of findings to human-robot interaction.

As pointed out in Section 4.4, the user studies performed on the muscle signal level have not included investigations regarding changes in limb pose. Since resistance to the **limb position effect** is essential for successful daily-life prosthetic usage, such an extension of the existing studies can be seen as a natural next step. For this purpose, the VR framework that we developed in the context of the VITA projects [v, w] could be used as a platform to perform user studies. In this or other VR environments, different conditions can be implemented and tested with a high level of immersion and embodiment.

On a similar note, the SATMC has been developed to be a general tool to assess and train myocontrol approaches. The study performed using the SATMC in Publication 4 applied a myocontroller with eight sEMG sensors and the algorithm described in Section 2.3.4. Joining the findings from the studies regarding sensor-modality fusion and transparent control with said algorithm could further improve myocontrol and user satisfaction. A multi-session user study with such a myocontroller is a feasible endeavour providing adequate hardware and an interested participant.

Based on our collective results, exploiting co-adaptation for myocontrol is a highly desirable concept. To build on this notion further, different features of EMG or other modalities could be investigated based on their capability to support transparent control. In our studies, we chose only to use the envelope of the sEMG or FMG signal as input to our myocontrol as this feature is intuitive and predictable for the user. However, further features could have similar or even better properties. A starting point for identifying relevant features can be the extensive review by Phinyomark et al. [53].

Moreover, unsupervised ML methods could further support co-adaptation in user training for myocontrol. Recently, incremental variants of these methods have been applied to myocontrol [267, 268]. Since they don't require labelled data, this potentially problematic step in myocontroller training is no longer required. Additionally, these synergy-based methods remove the constraint on the user to produce dedicated signals associated with specific actions. Instead of accidentally selecting actions that interfere with each other — as we have experienced in the user study of Publication 4 — unsupervised approaches extract independent components that can be used for myocontrol. An extension of these approaches with incrementality in the action set could lead to an improved control experience that could be assessed and trained using the SATMC.

Regarding the SATMC, we have experienced a few experimenter errors in the user study in Publication 4. The majority of steps in the protocol are described in the guidelines. Therefore, an automated SATMC execution could reduce potential errors. Pen and paper were used to collect the *visual analogue scale* scores. Replacing that with a digital medium could automatically determine the next task or indicate whether a new phase can be started.

Lastly, myocontrol has not only drawn inspiration from concepts originating from robotics, such as shared control [269, 270], but it was also used to interact with robotic devices [184, 234, 271, 272]. With the advent of cobots [273] and increasingly close collaboration between humans and robots [274, 275, 276], the concepts that have been developed for user and prosthesis interaction could be of benefit to the area of human-robot collaboration.

5.2 Perspective

A holistic approach combining scientific achievements involving novel control modalities and modern prosthetic devices with surgical techniques and appropriate training will provide users with the best prosthetic provisions. A person who has undergone TMR and was equipped with a multi-DOF prosthetic arm made the following statement:

> *When I use the new prosthesis, I just do things.*
> *I don't have to think about it.*
>
> Person with limb absence [277]

Bibliography

[1] Cordella, F., Ciancio, A. L., Sacchetti, R., Davalli, A., Cutti, A. G., Guglielmelli, E., Zollo, L., "Literature Review on Needs of Upper Limb Prosthesis Users". In: *Frontiers in Neuroscience* 10 (2016). DOI: 10.3389/fnins.2016.00209.

[2] Maat, B., Smit, G., Plettenburg, D., Breedveld, P., "Passive Prosthetic Hands and Tools: A Literature Review". In: *Prosthetics and Orthotics International* 42.1 (Feb. 2018), pp. 66–74. DOI: 10.1177/0309364617691622.

[3] Schweitzer, W., Thali, M. J., Egger, D., "Case-Study of a User-Driven Prosthetic Arm Design: Bionic Hand versus Customized Body-Powered Technology in a Highly Demanding Work Environment". In: *Journal of NeuroEngineering and Rehabilitation* 15.1 (Jan. 2018), p. 1. DOI: 10.1186/s12984-017-0340-0.

[4] Johannes, M. S., Bigelow, J. D., Burck, J. M., Harshbarger, S. D., Kozlowski, M. V., Van Doren, T., "An Overview of the Developmental Process for the Modular Prosthetic Limb". In: *Johns Hopkins APL Technical Digest* 30.3 (2011), pp. 207–216.

[5] Pohlig GmbH, *Types of Prostheses: Cosmetic, Myoelectric, Self-Powered.* https://www.pohlig.net/en/orthopedic-technology/treatment-solutions/prostheses-finger-hand-arm/types-of-prothesis. (accessed 2022-10-08).

[6] Schweitzer, W. *Technical below Elbow Amputee Issues - Body Powered Arms [Overview].* http://www.swisswuff.ch/tech/?p=2371. (accessed 2022-10-08). Nov. 2013.

[7] ToughWare PRX, *Vari-Pinch Prehensor™ (V2P™).* http://dev.toughwareprx.com/product/vari-pinch-prehensor-v2p/. (accessed 2022-10-08).

[8] Kyberd, P. J., Hill, W., "Survey of Upper Limb Prosthesis Users in Sweden, the United Kingdom and Canada". In: *Prosthetics and Orthotics International* 35.2 (June 2011), pp. 234–241. DOI: 10.1177/0309364611409099.

[9] Salminger, S., Stino, H., Pichler, L. H., Gstoettner, C., Sturma, A., Mayer, J. A., Szivak, M., Aszmann, O. C., "Current Rates of Prosthetic Usage in Upper-Limb Amputees – Have Innovations Had an Impact on Device Acceptance?" In: *Disability and Rehabilitation* 44.14 (Dec. 2020), pp. 3708–3713. DOI: 10.1080/09638288.2020.1866684.

[10] Peerdeman, B., Boere, D., Witteveen, H., Huis in 't Veld, R., Hermens, H., Stramigioli, S., Rietman, H., Veltink, P., Misra, S., "Myoelectric Forearm Prostheses: State of the Art from a User-Centered Perspective". In: *The Journal of Rehabilitation Research and Development* 48.6 (2011), p. 719. DOI: 10.1682/JRRD.2010.08.0161.

[11] Ottobock, *Technology for People 4.0: Ottobock at OTWorld 2018*. https://www.ottobock.com/en/newsroom/news/technology-for-people-4-0-ottobock-at-otworld-2018.html. (accessed 2020-10-05). May 2018.

[12] COAPT LLC, *COMPLETE CONTROL SYSTEM GEN2*. https://www.coaptengineering.com/wp-content/uploads/2021/09/Coapt-Gen2-Handbook-v5.2.pdf. (accessed 2022-08-01).

[13] Young, B. H. *I Have One of the Most Advanced Prosthetic Arms in the World — and I Hate It*. https://www.inputmag.com/culture/cyborg-chic-bionic-prosthetic-arm-sucks. (accessed 2022-10-06). Mar. 2021.

[14] Engdahl, S. M., Christie, B. P., Kelly, B., Davis, A., Chestek, C. A., Gates, D. H., "Surveying the Interest of Individuals with Upper Limb Loss in Novel Prosthetic Control Techniques". In: *Journal of NeuroEngineering and Rehabilitation* 12.1 (June 2015), p. 53. DOI: 10.1186/s12984-015-0044-2.

[15] Franzke, A. W., Kristoffersen, M. B., Bongers, R. M., Murgia, A., Pobatschnig, B., Unglaube, F., van der Sluis, C. K., "Users' and Therapists' Perceptions of Myoelectric Multi-Function Upper Limb Prostheses with Conventional and Pattern Recognition Control". In: *PLOS ONE* 14.8 (Aug. 2019), e0220899. DOI: 10.1371/journal.pone.0220899.

[16] Campbell, E., Phinyomark, A., Scheme, E. J., "Current Trends and Confounding Factors in Myoelectric Control: Limb Position and Contraction Intensity". In: *Sensors* 20.6 (Jan. 2020), p. 1613. DOI: 10.3390/s20061613.

[17] Scheme, E. J., Fougner, A., Stavdahl, Ø., Chan, A. D. C., Englehart, K. B., "Examining the Adverse Effects of Limb Position on Pattern Recognition Based Myoelectric Control". In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*. Buenos Aires: IEEE, Aug. 2010, pp. 6337–6340. DOI: 10.1109/IEMBS.2010.5627638.

[18] Merletti, R., Aventaggiato, M., Botter, A., Holobar, A., Marateb, H. R., Vieira, T. M. M., "Advances in Surface EMG: Recent Progress in Detection and Processing Techniques". In: *Critical Reviews in Biomedical Engineering* 38.4 (2010), pp. 305–345. DOI: 10.1615/CritRevBiomedEng.v38.i4.10.

[19] Biddiss, E. A., Chau, T. T., "Upper Limb Prosthesis Use and Abandonment: A Survey of the Last 25 Years". In: *Prosthetics and Orthotics International* 31.3 (Sept. 2007), pp. 236–257. DOI: 10.1080/03093640600994581.

[20] Jiang, N., Dosen, S., Müller, K.-R., Farina, D., "Myoelectric Control of Artificial Limbs—Is There a Need to Change Focus? [In the Spotlight]". In: *IEEE Signal Processing Magazine* 29.5 (Sept. 2012), pp. 152–150. DOI: 10.1109/MSP.2012.2203480.

[21] Franzke, A. W., Kristoffersen, M. B., Jayaram, V., van der Sluis, C. K., Murgia, A., Bongers, R. M., "Exploring the Relationship between EMG Feature Space Characteristics and Control Performance in Machine Learning Myoelectric Control". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* (2020), pp. 1–1. DOI: `10.1109/TNSRE.2020.3029873`.

[22] Teh, Y., Hargrove, L. J., "Offline Repeatability Correlates with Real-Time Performance of Pattern Recognition Controllers". In: *ICNR 2020.* 2020, p. 2.

[23] *CYBATHLON.* `https://cybathlon.ethz.ch/en`. (accessed 2022-10-12).

[24] *Cybathlon — Official Image Library.* `https://www.skyfish.com/p/cybathlon`. (accessed 2022-10-13).

[25] Schünke, M., Schulte, E., Schumacher, U., *Prometheus.* Georg Thieme Verlag, 2005.

[26] Betts, J. G., Young, K. A., Wise, J. A., Johnson, E., Poe, B., Kruse, D. H., Korol, O., Johnson, J. E., Womble, M., DeSaix, P., *Anatomy and Physiology.* 2013.

[27] *Teaching Modules and On-Line Courses Roberto Merletti PhD.* `https://www.robertomerletti.it/en/emg/material/teaching/`. (accessed 2022-10-14).

[28] *Integrative Biomedical Lab.* `http://hit-micrscopewb.hc.msu.edu/VIPL/VIL-New/VIL-Week03/VIL-W03_Top_05_01.html`. (accessed 2022-10-14).

[29] Schiaffino, S., Reggiani, C., "Fiber Types in Mammalian Skeletal Muscles". In: *Physiological Reviews* 91.4 (Oct. 2011), pp. 1447–1531. DOI: `10.1152/physrev.00031.2010`.

[30] Milner-Brown, H. S., Stein, R. B., Yemm, R., "The Orderly Recruitment of Human Motor Units during Voluntary Isometric Contractions". In: *The Journal of Physiology* 230.2 (1973), pp. 359–370. DOI: `10.1113/jphysiol.1973.sp010192`.

[31] Henneman, E. "The Size-Principle: A Deterministic Output Emerges from a Set of Probabilistic Connections". In: *Journal of Experimental Biology* 115.1 (Mar. 1985), pp. 105–112. DOI: `10.1242/jeb.115.1.105`.

[32] De Luca, C. J., Contessa, P., "Hierarchical Control of Motor Units in Voluntary Contractions". In: *Journal of Neurophysiology* 107.1 (Jan. 2012), pp. 178–195. DOI: `10.1152/jn.00961.2010`.

[33] De Luca, C. J., Contessa, P., "Biomechanical Benefits of the Onion-Skin Motor Unit Control Scheme". In: *Journal of Biomechanics* 48.2 (Jan. 2015), pp. 195–203. DOI: `10.1016/j.jbiomech.2014.12.003`.

[34] Huxley, H. E. "The Mechanism of Muscular Contraction". In: *Scientific American* 213.6 (1965), pp. 18–27.

[35] Rayment, I., Holden, H. M., Whittaker, M., Yohn, C. B., Lorenz, M., Holmes, K. C., Milligan, R. A., "Structure of the Actin-Myosin Complex and Its Implications for Muscle Contraction". In: *Science* 261.5117 (July 1993), pp. 58–65. DOI: `10.1126/science.8316858`.

[36] Farina, D., Cescon, C., Merletti, R., "Influence of Anatomical, Physical, and Detection-System Parameters on Surface EMG". In: *Biological Cybernetics* 86.6 (June 2002), pp. 445–456. DOI: 10.1007/s00422-002-0309-2.

[37] Farina, D., Jiang, N., Rehbaum, H., Holobar, A., Graimann, B., Dietl, H., Aszmann, O. C., "The Extraction of Neural Information from the Surface EMG for the Control of Upper-Limb Prostheses: Emerging Avenues and Challenges". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.4 (July 2014), pp. 797–809. DOI: 10.1109/TNSRE.2014.2305111.

[38] De Luca, C. J. "The Use of Surface Electromyography in Biomechanics". In: *Journal of Applied Biomechanics* 13.2 (May 1997), pp. 135–163. DOI: 10.1123/jab.13.2.135.

[39] Merletti, R., Parker, P. J., *Electromyography: Physiology, Engineering, and Non-Invasive Applications*. John Wiley & Sons, July 2004.

[40] Merletti, R., Farina, D., "Analysis of Intramuscular Electromyogram Signals". In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 367.1887 (Jan. 2009), pp. 357–368. DOI: 10.1098/rsta.2008.0235.

[41] Cipriani, C., Segil, J. L., Birdwell, J. A., Weir, R. F., "Dexterous Control of a Prosthetic Hand Using Fine-Wire Intramuscular Electrodes in Targeted Extrinsic Muscles". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.4 (July 2014), pp. 828–836. DOI: 10.1109/TNSRE.2014.2301234.

[42] Pasquina, P. F., Evangelista, M., Carvalho, A. J., Lockhart, J., Griffin, S., Nanos, G. P., McKay, P., Hansen, M., Ipsen, D., Vandersea, J., Butkus, J., Miller, M., Murphy, I., Hankin, D., "First-in-Man Demonstration of a Fully Implanted Myoelectric Sensors System to Control an Advanced Electromechanical Prosthetic Hand". In: *Journal of Neuroscience Methods*. Brain Computer Interfaces; Tribute to Greg A. Gerhardt 244 (Apr. 2015), pp. 85–93. DOI: 10.1016/j.jneumeth.2014.07.016.

[43] Hahne, J. M., Farina, D., Jiang, N., Liebetanz, D., "A Novel Percutaneous Electrode Implant for Improving Robustness in Advanced Myoelectric Control". In: *Frontiers in Neuroscience* 10 (2016).

[44] Weir, R. F., Troyk, P. R., DeMichele, G., Kuiken, T. A., "Implantable Myoelectric Sensors (IMES) for Upper-Extremity Prosthesis Control- Preliminary Work". In: *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No.03CH37439)*. Vol. 2. Sept. 2003, 1562–1565 Vol.2. DOI: 10.1109/IEMBS.2003.1279658.

[45] Ortiz-Catalan, M., Håkansson, B., Brånemark, R., "An Osseointegrated Human-Machine Gateway for Long-Term Sensory Feedback and Motor Control of Artificial Limbs". In: *Science Translational Medicine* 6.257 (Oct. 2014), 257re6–257re6. DOI: 10.1126/scitranslmed.3008933.

[46] De Luca, C. J., Merletti, R., “Surface Myoelectric Signal Cross-Talk among Muscles of the Leg”. In: *Electroencephalography and Clinical Neurophysiology* 69.6 (June 1988), pp. 568–575. DOI: `10.1016/0013-4694(88)90169-1`.

[47] Farina, D., Merletti, R., Enoka, R. M., “The Extraction of Neural Strategies from the Surface EMG”. In: *Journal of Applied Physiology* 96.4 (Apr. 2004), pp. 1486–1495. DOI: `10.1152/japplphysiol.01070.2003`.

[48] Merletti, R., Muceli, S., “Tutorial. Surface EMG Detection in Space and Time: Best Practices”. In: *Journal of Electromyography and Kinesiology* 49 (Dec. 2019), p. 102363. DOI: `10.1016/j.jelekin.2019.102363`.

[49] Micera, S., Carpaneto, J., Raspopovic, S., “Control of Hand Prostheses Using Peripheral Information”. In: *IEEE Reviews in Biomedical Engineering* 3 (2010), pp. 48–68. DOI: `10.1109/RBME.2010.2085429`.

[50] Kiernan, M. C., Vucic, S., Cheah, B. C., Turner, M. R., Eisen, A., Hardiman, O., Burrell, J. R., Zoing, M. C., “Amyotrophic Lateral Sclerosis”. In: *The Lancet* 377.9769 (Mar. 2011), pp. 942–955. DOI: `10.1016/S0140-6736(10)61156-7`.

[51] Hudgins, B. S., Parker, P. A., Scott, R. N., “A New Strategy for Multifunction Myoelectric Control”. In: *IEEE Transactions on Biomedical Engineering* 40.1 (Jan. 1993), pp. 82–94. DOI: `10.1109/10.204774`.

[52] Phinyomark, A., Phukpattaranont, P., Limsakul, C., “Feature Reduction and Selection for EMG Signal Classification”. In: *Expert Systems with Applications* 39.8 (June 2012), pp. 7420–7431. DOI: `10.1016/j.eswa.2012.01.102`.

[53] Phinyomark, A., Khushaba, R. N., Ibáñez-Marcelo, E., Patania, A., Scheme, E. J., Petri, G., “Navigating Features: A Topologically Informed Chart of Electromyographic Features Space”. In: *Journal of The Royal Society Interface* 14.137 (Dec. 2017), p. 20170734. DOI: `10.1098/rsif.2017.0734`.

[54] Phinyomark, A., Khushaba, R. N., Scheme, E. J., “Feature Extraction and Selection for Myoelectric Control Based on Wearable EMG Sensors”. In: *Sensors* 18.5 (May 2018), p. 1615. DOI: `10.3390/s18051615`.

[55] McGill, K. C., Lateva, Z. C., Marateb, H. R., “EMGLAB: An Interactive EMG Decomposition Program”. In: *Journal of Neuroscience Methods* 149.2 (Dec. 2005), pp. 121–133. DOI: `10.1016/j.jneumeth.2005.05.015`.

[56] Holobar, A., Zazula, D., “Multichannel Blind Source Separation Using Convolution Kernel Compensation”. In: *IEEE Transactions on Signal Processing* 55.9 (Sept. 2007), pp. 4487–4496. DOI: `10.1109/TSP.2007.896108`.

[57] Chen, M., Zhou, P., “A Novel Framework Based on FastICA for High Density Surface EMG Decomposition”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 24.1 (Jan. 2016), pp. 117–127. DOI: `10.1109/TNSRE.2015.2412038`.

[58] Negro, F., Muceli, S., Castronovo, A. M., Holobar, A., Farina, D., "Multi-Channel Intramuscular and Surface EMG Decomposition by Convolutive Blind Source Separation". In: *Journal of Neural Engineering* 13.2 (Apr. 2016), p. 026027. DOI: 10.1088/1741-2560/13/2/026027.

[59] Holobar, A., Minetto, M. A., Farina, D., "Accurate Identification of Motor Unit Discharge Patterns from High-Density Surface EMG and Validation with a Novel Signal-Based Performance Metric". In: *Journal of Neural Engineering* 11.1 (Jan. 2014), p. 016008. DOI: 10.1088/1741-2560/11/1/016008.

[60] Farina, D., Colombo, R., Merletti, R., Baare Olsen, H., "Evaluation of Intra-Muscular EMG Signal Decomposition Algorithms". In: *Journal of Electromyography and Kinesiology* 11.3 (June 2001), pp. 175–187. DOI: 10.1016/S1050-6411(00)00051-1.

[61] Nawab, S. H., Wotiz, R. P., De Luca, C. J., "Decomposition of Indwelling EMG Signals". In: *Journal of Applied Physiology* 105.2 (Aug. 2008), pp. 700–710. DOI: 10.1152/japplphysiol.00170.2007.

[62] Florestal, J. R., Mathieu, P. A., Malanda, A., "Automated Decomposition of Intramuscular Electromyographic Signals". In: *IEEE Transactions on Biomedical Engineering* 53.5 (May 2006), pp. 832–839. DOI: 10.1109/TBME.2005.863893.

[63] De Luca, C. J., Adam, A., Wotiz, R. P., Gilmore, L. D., Nawab, S. H., "Decomposition of Surface EMG Signals". In: *Journal of Neurophysiology* 96.3 (Sept. 2006), pp. 1646–1657. DOI: 10.1152/jn.00009.2006.

[64] Farina, D., Negro, F., Gazzoni, M., Enoka, R. M., "Detecting the Unique Representation of Motor-Unit Action Potentials in the Surface Electromyogram". In: *Journal of Neurophysiology* 100.3 (Sept. 2008), pp. 1223–1233. DOI: 10.1152/jn.90219.2008.

[65] Farina, D., Holobar, A., Merletti, R., Enoka, R. M., "Decoding the Neural Drive to Muscles from the Surface Electromyogram". In: *Clinical Neurophysiology* 121.10 (Oct. 2010), pp. 1616–1623. DOI: 10.1016/j.clinph.2009.10.040.

[66] Farina, D., Enoka, R. M., "Surface EMG Decomposition Requires an Appropriate Validation". In: *Journal of Neurophysiology* 105.2 (Feb. 2011), pp. 981–982. DOI: 10.1152/jn.00855.2010.

[67] Muceli, S., Poppendieck, W., Negro, F., Yoshida, K., Hoffmann, K.-P., Butler, J. E., Gandevia, S. C., Farina, D., "Accurate and Representative Decoding of the Neural Drive to Muscles in Humans with Multi-Channel Intramuscular Thin-Film Electrodes". In: *The Journal of Physiology* 593.17 (2015), pp. 3789–3804. DOI: 10.1113/JP270902.

[68] Hug, F., Avrillon, S., Ibáñez, J., Farina, D., "Common Synaptic Input, Synergies and Size Principle: Control of Spinal Motor Neurons for Movement Generation". In: *The Journal of Physiology* 601.1 (2023), pp. 11–20. DOI: 10.1113/JP283698.

[69] Kuiken, T. A., Miller, L. A., Lipschutz, R. D., Lock, B. A., Stubblefield, K. A., Marasco, P. D., Zhou, P., Dumanian, G. A., “Targeted Reinnervation for Enhanced Prosthetic Arm Function in a Woman with a Proximal Amputation: A Case Study”. In: *The Lancet* 369.9559 (Feb. 2007), pp. 371–380. DOI: 10.1016/S0140-6736(07)60193-7.

[70] Kuiken, T. A., Li, G., Lock, B. A., Lipschutz, R. D., Miller, L. A., Stubblefield, K. A., Englehart, K. B., “Targeted Muscle Reinnervation for Real-time Myoelectric Control of Multifunction Artificial Arms”. In: *JAMA* 301.6 (Feb. 2009), pp. 619–628. DOI: 10.1001/jama.2009.116.

[71] Gart, M. S., Souza, J. M., Dumanian, G. A., “Targeted Muscle Reinnervation in the Upper Extremity Amputee: A Technical Roadmap”. In: *Journal of Hand Surgery* 40.9 (Sept. 2015), pp. 1877–1888. DOI: 10.1016/j.jhsa.2015.06.119.

[72] Aszmann, O. C., Roche, A. D., Salminger, S., Paternostro-Sluga, T., Herceg, M., Sturma, A., Hofer, C., Farina, D., “Bionic Reconstruction to Restore Hand Function after Brachial Plexus Injury: A Case Series of Three Patients”. In: *The Lancet* 385.9983 (May 2015), pp. 2183–2189. DOI: 10.1016/S0140-6736(14)61776-1.

[73] Marasco, P. D., Schultz, A. E., Kuiken, T. A., “Sensory Capacity of Reinnervated Skin after Redirection of Amputated Upper Limb Nerves to the Chest”. In: *Brain* 132.6 (June 2009), pp. 1441–1448. DOI: 10.1093/brain/awp082.

[74] Marasco, P. D., Kim, K., Colgate, J. E., Peshkin, M. A., Kuiken, T. A., “Robotic Touch Shifts Perception of Embodiment to a Prosthesis in Targeted Reinnervation Amputees”. In: *Brain* 134.3 (Mar. 2011), pp. 747–758. DOI: 10.1093/brain/awq361.

[75] Souza, J. M., Cheesborough, J. E., Ko, J. H., Cho, M. S., Kuiken, T. A., Dumanian, G. A., “Targeted Muscle Reinnervation: A Novel Approach to Postamputation Neuroma Pain”. In: *Clinical Orthopaedics and Related Research®* 472.10 (Oct. 2014), pp. 2984–2990. DOI: 10.1007/s11999-014-3528-7.

[76] Valerio, I. L., Dumanian, G. A., Jordan, S. W., Mioton, L. M., Bowen, J. B., West, J. M., Porter, K., Ko, J. H., Souza, J. M., Potter, B. K., “Preemptive Treatment of Phantom and Residual Limb Pain with Targeted Muscle Reinnervation at the Time of Major Limb Amputation”. In: *Journal of the American College of Surgeons* 228.3 (Mar. 2019), pp. 217–226. DOI: 10.1016/j.jamcollsurg.2018.12.015.

[77] Dumanian, G. A., Potter, B. K., Mioton, L. M., Ko, J. H., Cheesborough, J. E., Souza, J. M., Ertl, W. J., Tintle, S. M., Nanos, G. P., Valerio, I. L., Kuiken, T. A., Apkarian, A. V., Porter, K., Jordan, S. W., “Targeted Muscle Reinnervation Treats Neuroma and Phantom Pain in Major Limb Amputees: A Randomized Clinical Trial”. In: *Annals of Surgery* 270.2 (Aug. 2019), pp. 238–246. DOI: 10.1097/SLA.0000000000003088.

[78] Farina, D., Vujaklija, I., Brånemark, R., Bull, A. M. J., Dietl, H., Graimann, B., Hargrove, L. J., Hoffmann, K.-P., Huang, H. (, Ingvarsson, T., Janusson, H. B., Kristjánsson, K., Kuiken, T. A., Micera, S., Stieglitz, T., Sturma, A., Tyler, D. J., Weir, R. F., Aszmann, O. C., "Toward Higher-Performance Bionic Limbs for Wider Clinical Use". In: *Nature Biomedical Engineering* (May 2021). DOI: 10.1038/s41551-021-00732-x.

[79] Gray, H. *Anatomy of the Human Body*. Lea & Febiger, 1878.

[80] Abboudi, R. L., Glass, C. A., Newby, N. A., Flint, J. A., Craelius, W., "A Biomimetic Controller for a Multifinger Prosthesis". In: *IEEE Transactions on Rehabilitation Engineering* 7.2 (June 1999), pp. 121–129. DOI: 10.1109/86.769401.

[81] Craelius, W. "The Bionic Man: Restoring Mobility". In: *Science* 295.5557 (Feb. 2002), pp. 1018–1021. DOI: 10.1126/science.295.5557.1018.

[82] Phillips, S. L., Craelius, W., "Residual Kinetic Imaging: A Versatile Interface for Prosthetic Control". In: *Robotica* 23.3 (May 2005), pp. 277–282. DOI: 10.1017/S0263574704001298.

[83] Lukowicz, P., Hanser, F., Szubski, C., Schobersberger, W., "Detecting and Interpreting Muscle Activity with Wearable Force Sensors". In: *Pervasive Computing*. Vol. 3968. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 101–116. DOI: 10.1007/11748625_7.

[84] Wininger, M. T., Kim, N.-H., Craelius, W., "Pressure Signature of Forearm as Predictor of Grip Force". In: *Journal of Rehabilitation Research and Development* 45.6 (2008), pp. 883–892. DOI: 10.1682/jrrd.2007.11.0187.

[85] Cho, E., Chen, R., Merhi, L.-K., Xiao, Z., Pousett, B., Menon, C., "Force Myography to Control Robotic Upper Extremity Prostheses: A Feasibility Study". In: *Frontiers in Bioengineering and Biotechnology* 4 (2016).

[86] Jiang, X., Merhi, L.-K., Xiao, Z. G., Menon, C., "Exploration of Force Myography and Surface Electromyography in Hand Gesture Classification". In: *Medical Engineering & Physics* 41 (Mar. 2017), pp. 63–73. DOI: 10.1016/j.medengphy.2017.01.015.

[87] Anvaripour, M., Khoshnam, M., Menon, C., Saif, M., "FMG- and RNN-Based Estimation of Motor Intention of Upper-Limb Motion in Human-Robot Collaboration". In: *Frontiers in Robotics and AI* 7 (2020), p. 183. DOI: 10.3389/frobt.2020.573096.

[88] Radmand, A., Scheme, E. J., Englehart, K. B., "High-Density Force Myography: A Possible Alternative for Upper-Limb Prosthetic Control". In: *Journal of Rehabilitation Research and Development* 53.4 (2016), pp. 443–456. DOI: 10.1682/JRRD.2015.03.0041.

[89] Ahmadizadeh, C., Merhi, L.-K., Pousett, B., Sangha, S., Menon, C., "Toward Intuitive Prosthetic Control: Solving Common Issues Using Force Myography, Surface Electromyography, and Pattern Recognition in a Pilot Case Study". In: *IEEE Robotics & Automation Magazine* 24.4 (Dec. 2017), pp. 102–111. DOI: 10.1109/MRA.2017.2747899.

[90] Xiao, Z. G., Menon, C., "A Review of Force Myography Research and Development". In: *Sensors* 19.20 (Jan. 2019), p. 4557. DOI: 10.3390/s19204557.

[91] Xiao, Z. G., Menon, C., "An Investigation on the Sampling Frequency of the Upper-Limb Force Myographic Signals". In: *Sensors* 19.11 (May 2019), p. 2432. DOI: 10.3390/s19112432.

[92] Castellini, C., Kõiva, R., Pasluosta, C., de Oliveira Viegas, C. L., Eskofier, B. M., "Tactile Myography: An off-Line Assessment on Intact Subjects and One Upper-Limb Disabled". In: *Technologies / SI: Assistive Robotics* 6.2 (2018).

[93] Connan, M., Kõiva, R., Castellini, C., "Online Natural Myocontrol of Combined Hand and Wrist Actions Using Tactile Myography and the Biomechanics of Grasping". In: *Frontiers in Neurorobotics* 14 (Feb. 2020), p. 11. DOI: 10.3389/fnbot.2020.00011.

[94] Castellini, C., Artemiadis, P. K., Wininger, M. T., Ajoudani, A., Alimusaj, M., Bicchi, A., Caputo, B., Craelius, W., Dosen, S., Englehart, K. B., Farina, D., Gijsberts, A., Godfrey, S. B., Hargrove, L. J., Ison, M., Kuiken, T. A., Marković, M., Pilarski, P. M., Rupp, R., Scheme, E. J., "Proceedings of the First Workshop on Peripheral Machine Interfaces: Going beyond Traditional Surface Electromyography". In: *Frontiers in Neurorobotics* 8 (2014).

[95] Sierotowicz, M., Brusamento, D., Schirrmeister, B., Connan, M., Bornmann, J., Gonzalez-Vargas, J., Castellini, C., "Unobtrusive, Natural Support Control of an Adaptive Industrial Exoskeleton Using Force Myography". In: *Frontiers in Robotics and AI* 9 (2022).

[96] Ravindra, V., Castellini, C., "A Comparative Analysis of Three Non-Invasive Human-Machine Interfaces for the Disabled". In: *Frontiers in Neurorobotics* 8 (Oct. 2014). DOI: 10.3389/fnbot.2014.00024.

[97] Connan, M., Ruiz Ramírez, E., Vodermayer, B., Castellini, C., "Assessment of a Wearable Force- and Electromyography Device and Comparison of the Related Signals for Myocontrol". In: *Frontiers in Neurorobotics* 10 (Nov. 2016). DOI: 10.3389/fnbot.2016.00017.

[98] Li, N., Yang, D., Jiang, L., Liu, H., Cai, H., "Combined Use of FSR Sensor Array and SVM Classifier for Finger Motion Recognition Based on Pressure Distribution Map". In: *Journal of Bionic Engineering* 9.1 (Mar. 2012), pp. 39–47. DOI: 10.1016/S1672-6529(11)60095-4.

[99] Kõiva, R., Riedenklau, E., de Oliveira Viegas, C. L., Castellini, C., "Shape Conformable High Spatial Resolution Tactile Bracelet for Detecting Hand and Wrist Activity". In: *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*. Aug. 2015, pp. 157–162. DOI: 10.1109/ICORR.2015.7281192.

[100] Gordon, G., Holbourn, A. H. S., "The Sounds from Single Motor Units in a Contracting Muscle". In: *The Journal of Physiology* 107.4 (1948), pp. 456–464. DOI: 10.1113/jphysiol.1948.sp004290.

[101] Barry, D. T., Geiringer, S. R., Ball, R. D., "Acoustic Myography: A Noninvasive Monitor of Motor Unit Fatigue". In: *Muscle & Nerve* 8.3 (1985), pp. 189–194. DOI: 10.1002/mus.880080303.

[102] Fara, S., Vikram, C. S., Gavriel, C., Faisal, A. A., "Robust, Ultra Low-Cost MMG System with Brain-Machine-Interface Applications". In: *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)*. Nov. 2013, pp. 723–726. DOI: 10.1109/NER.2013.6696036.

[103] Wang, D., Xie, C., Wu, H., Hu, D., Zhang, Q., Gao, L., "Estimation of Knee Extension Force Using Mechanomyography Signals Detected Through Clothing". In: *Intelligent Robotics and Applications*. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2019, pp. 3–14. DOI: 10.1007/978-3-030-27532-7_1.

[104] Sierra González, D., Castellini, C., "A Realistic Implementation of Ultrasound Imaging as a Human-Machine Interface for Upper-Limb Amputees". In: *Frontiers in Neurorobotics* 7 (2013).

[105] Zhang, Y., Harrison, C., "Tomo: Wearable, Low-Cost Electrical Impedance Tomography for Hand Gesture Recognition". In: *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*. Charlotte NC USA: ACM, Nov. 2015, pp. 167–173. DOI: 10.1145/2807442.2807480.

[106] Zhang, Y., Xiao, R., Harrison, C., "Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography". In: *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*. Tokyo Japan: ACM, Oct. 2016, pp. 843–850. DOI: 10.1145/2984511.2984574.

[107] Wu, Y., Jiang, D., Duan, J., Liu, X., Bayford, R., Demosthenous, A., "Towards a High Accuracy Wearable Hand Gesture Recognition System Using EIT". In: *2018 IEEE International Symposium on Circuits and Systems (ISCAS)*. Florence: IEEE, 2018, pp. 1–4. DOI: 10.1109/ISCAS.2018.8351296.

[108] Connan, M., Yu, B., Gibas, C., Brück, R., Kirchner, E. A., Castellini, C., "Deep and Surface Sensor Modalities for Myo-Intent Detection". In: *Proceedings of MEC - Myoelectric Control Symposium*. 2022.

[109] Acuña, S., Engdahl, S. M., Bashatah, A., Otto, P., Kaliki, R. R., Sikdar, S., "A Wearable Sonomyography System for Prosthesis Control". In: *Proceedings of MEC - Myoelectric Control Symposium*. 2022.

[110] Engdahl, S., Acuña, S., Bashatah, A., Dhawan, A., King, E., Mukherjee, B., Holley, R., Monroe, B., Lévay, G., Kaliki, R. R., Sikdar, S., "Assessing the Feasibility of Using Sonomyography for Upper Limb Prosthesis Control". In: *Proceedings of MEC - Myoelectric Control Symposium.* 2022.

[111] Gibas, C., Grünewald, A., Büchner, S., Brück, R., "An EIT System for Mobile Medical Diagnostics". In: *Medical Imaging 2018: Biomedical Applications in Molecular, Structural, and Functional Imaging.* Vol. 10578. SPIE, Mar. 2018, pp. 567–575. DOI: 10.1117/12.2295886.

[112] Englehart, K. B., Hudgins, B. S., Parker, P. A., Stevenson, M., "Classification of the Myoelectric Signal Using Time-Frequency Based Representations". In: *Medical Engineering & Physics* 21.6 (July 1999), pp. 431–438. DOI: 10.1016/S1350-4533(99)00066-1.

[113] Englehart, K. B., Hudgin, B. S., Parker, P. A., "A Wavelet-Based Continuous Classification Scheme for Multifunction Myoelectric Control". In: *IEEE Transactions on Biomedical Engineering* 48.3 (Mar. 2001), pp. 302–311. DOI: 10.1109/10.914793.

[114] Englehart, K. B., Hudgins, B. S., "A Robust, Real-Time Control Scheme for Multifunction Myoelectric Control". In: *IEEE Transactions on Biomedical Engineering* 50.7 (July 2003), pp. 848–854. DOI: 10.1109/TBME.2003.813539.

[115] Scheme, E. J., Englehart, K. B., "Electromyogram Pattern Recognition for Control of Powered Upper-Limb Prostheses: State of the Art and Challenges for Clinical Use". In: *The Journal of Rehabilitation Research and Development* 48.6 (2011), p. 643. DOI: 10.1682/JRRD.2010.09.0177.

[116] Fougner, A., Stavdahl, Ø., Kyberd, P. J., Losier, Y. G., Parker, P. A., "Control of Upper Limb Prostheses: Terminology and Proportional Myoelectric Control—A Review". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 20.5 (Sept. 2012), pp. 663–677. DOI: 10.1109/TNSRE.2012.2196711.

[117] Kaufmann, P., Englehart, K. B., Platzner, M., "Fluctuating Emg Signals: Investigating Long-Term Effects of Pattern Matching Algorithms". In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology.* Aug. 2010, pp. 6357–6360. DOI: 10.1109/IEMBS.2010.5627288.

[118] Chu, J.-U., Moon, I., Lee, Y.-J., Kim, S.-K., Mun, M.-S., "A Supervised Feature-Projection-Based Real-Time EMG Pattern Recognition for Multifunction Myoelectric Hand Control". In: *IEEE/ASME Transactions on Mechatronics* 12.3 (June 2007), pp. 282–290. DOI: 10.1109/TMECH.2007.897262.

[119] Tenore, F. V. G., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, R., Thakor, N. V., "Decoding of Individuated Finger Movements Using Surface Electromyography". In: *IEEE Transactions on Biomedical Engineering* 56.5 (May 2009), pp. 1427–1434. DOI: 10.1109/TBME.2008.2005485.

[120] Park, S.-H., Lee, S.-P., “EMG Pattern Recognition Based on Artificial Intelligence Techniques”. In: *IEEE Transactions on Rehabilitation Engineering* 6.4 (Dec. 1998), pp. 400–405. DOI: 10.1109/86.736154.

[121] Micera, S., Sabatini, A. M., Dario, P., Rossi, B., “A Hybrid Approach to EMG Pattern Analysis for Classification of Arm Movements Using Statistical and Fuzzy Techniques”. In: *Medical Engineering & Physics* 21.5 (June 1999), pp. 303–311. DOI: 10.1016/S1350-4533(99)00055-7.

[122] Chan, F. H. Y., Yang, Y.-S., Lam, F. K., Zhang, Y.-T., Parker, P. A., “Fuzzy EMG Classification for Prosthesis Control”. In: *IEEE Transactions on Rehabilitation Engineering* 8.3 (Sept. 2000), pp. 305–311. DOI: 10.1109/86.867872.

[123] Ajiboye, A. B., Weir, R. F., “A Heuristic Fuzzy Logic Approach to EMG Pattern Recognition for Multifunctional Prosthesis Control”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 13.3 (Sept. 2005), pp. 280–291. DOI: 10.1109/TNSRE.2005.847357.

[124] Oskoei, M. A., Hu, H., “Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb”. In: *IEEE Transactions on Biomedical Engineering* 55.8 (Aug. 2008), pp. 1956–1965. DOI: 10.1109/TBME.2008.919734.

[125] Yang, D., Zhao, J., Gu, Y., Jiang, L., Liu, H., “EMG Pattern Recognition and Grasping Force Estimation: Improvement to the Myocontrol of Multi-DOF Prosthetic Hands”. In: *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. Oct. 2009, pp. 516–521. DOI: 10.1109/IROS.2009.5354544.

[126] Liu, Y.-H., Huang, H.-P., Weng, C.-H., “Recognition of Electromyographic Signals Using Cascaded Kernel Learning Machine”. In: *IEEE/ASME Transactions on Mechatronics* 12.3 (June 2007), pp. 253–264. DOI: 10.1109/TMECH.2007.897253.

[127] Shenoy, P., Miller, K. J., Crawford, B., Rao, R. P. N., “Online Electromyographic Control of a Robotic Prosthesis”. In: *IEEE Transactions on Biomedical Engineering* 55.3 (Mar. 2008), pp. 1128–1135. DOI: 10.1109/TBME.2007.909536.

[128] Chan, A. D. C., Englehart, K. B., “Continuous Myoelectric Control for Powered Prostheses Using Hidden Markov Models”. In: *IEEE Transactions on Biomedical Engineering* 52.1 (Jan. 2005), pp. 121–124. DOI: 10.1109/TBME.2004.836492.

[129] Zhang, X., Chen, X., Li, Y., Lantz, V., Wang, K., Yang, J., “A Framework for Hand Gesture Recognition Based on Accelerometer and EMG Sensors”. In: *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 41.6 (Nov. 2011), pp. 1064–1076. DOI: 10.1109/TSMCA.2011.2116004.

[130] Huang, Y., Englehart, K. B., Hudgins, B. S., Chan, A. D. C., “A Gaussian Mixture Model Based Classification Scheme for Myoelectric Control of Powered Upper Limb Prostheses”. In: *IEEE Transactions on Biomedical Engineering* 52.11 (Nov. 2005), pp. 1801–1811. DOI: 10.1109/TBME.2005.856295.

[131] Chu, J.-U., Lee, Y.-J., “Conjugate-Prior-Penalized Learning of Gaussian Mixture Models for Multifunction Myoelectric Hand Control”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 17.3 (June 2009), pp. 287–297. DOI: 10.1109/TNSRE.2009.2015177.

[132] Jiang, N., Englehart, K. B., Parker, P. A., “Extracting Simultaneous and Proportional Neural Control Information for Multiple-DOF Prostheses From the Surface Electromyographic Signal”. In: *IEEE Transactions on Biomedical Engineering* 56.4 (Apr. 2009), pp. 1070–1080. DOI: 10.1109/TBME.2008.2007967.

[133] Lock, B. A., Englehart, K. B., Hudgins, B. S. “Real-Time Myoelectric Control in a Virtual Environment to Relate Usability vs. Accuracy”. In: *MyoElectric Controls / Powered Prosthetics Symposium (MEC)* (2005), pp. 112–115.

[134] Amsüss, S., Goebel, P., Graimann, B., Farina, D., “A Multi-Class Proportional Myocontrol Algorithm for Upper Limb Prosthesis Control: Validation in Real-Life Scenarios on Amputees”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 23.5 (Sept. 2015), pp. 827–836. DOI: 10.1109/TNSRE.2014.2361478.

[135] Young, A. J., Smith, L. H., Rouse, E. J., Hargrove, L. J., “A New Hierarchical Approach for Simultaneous Control of Multi-Joint Powered Prostheses”. In: *2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob).* June 2012, pp. 514–520. DOI: 10.1109/BioRob.2012.6290709.

[136] Ameri, A., Scheme, E. J., Kamavuako, E. N., Englehart, K. B., Parker, P. A., “Real-Time, Simultaneous Myoelectric Control Using Force and Position-Based Training Paradigms”. In: *IEEE Transactions on Biomedical Engineering* 61.2 (Feb. 2014), pp. 279–287. DOI: 10.1109/TBME.2013.2281595.

[137] Lee, D. D., Seung, H. S., “Algorithms for Non-Negative Matrix Factorization”. In: *Advances in Neural Information Processing Systems.* 2001, pp. 556–562.

[138] d’Avella, A., Portone, A., Fernandez, L., Lacquaniti, F., “Control of Fast-Reaching Movements by Muscle Synergy Combinations”. In: *Journal of Neuroscience* 26.30 (July 2006), pp. 7791–7810. DOI: 10.1523/JNEUROSCI.0830-06.2006.

[139] Muceli, S., Jiang, N., Farina, D., “Extracting Signals Robust to Electrode Number and Shift for Online Simultaneous and Proportional Myoelectric Control by Factorization Algorithms”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.3 (May 2014), pp. 623–633. DOI: 10.1109/TNSRE.2013.2282898.

[140] Rehbaum, H., Jiang, N., Paredes, L., Amsüss, S., Graimann, B., Farina, D., “Real Time Simultaneous and Proportional Control of Multiple Degrees of Freedom from Surface EMG: Preliminary Results on Subjects with Limb Deficiency”. In: *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society.* Aug. 2012, pp. 1346–1349. DOI: 10.1109/EMBC.2012.6346187.

[141] Jiang, N., Rehbaum, H., Vujaklija, I., Graimann, B., Farina, D., "Intuitive, Online, Simultaneous, and Proportional Myoelectric Control Over Two Degrees-of-Freedom in Upper Limb Amputees". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.3 (May 2014), pp. 501–510. DOI: 10.1109/TNSRE.2013.2278411.

[142] Ameri, A., Kamavuako, E. N., Scheme, E. J., Englehart, K. B., Parker, P. A., "Support Vector Regression for Improved Real-Time, Simultaneous Myoelectric Control". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.6 (Nov. 2014), pp. 1198–1209. DOI: 10.1109/TNSRE.2014.2323576.

[143] Hahne, J. M., Rehbaum, H., Biessmann, F., Meinecke, F. C., Müller, K.-R., Jiang, N., Farina, D., Parra, L. C., "Simultaneous and Proportional Control of 2D Wrist Movements with Myoelectric Signals". In: *2012 IEEE International Workshop on Machine Learning for Signal Processing.* Sept. 2012, pp. 1–6. DOI: 10.1109/MLSP.2012.6349712.

[144] Hahne, J. M., Biebmann, F., Jiang, N., Rehbaum, H., Farina, D., Meinecke, F. C., Müller, K.-R., Parra, L. C., "Linear and Nonlinear Regression Techniques for Simultaneous and Proportional Myoelectric Control". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.2 (Mar. 2014), pp. 269–279. DOI: 10.1109/TNSRE.2014.2305520.

[145] Vest-Nielsen, J. L. G., Holmgaard, S., Jiang, N., Englehart, K. B., Farina, D., Parker, P. A., "Simultaneous and Proportional Force Estimation for Multifunction Myoelectric Prostheses Using Mirrored Bilateral Training". In: *IEEE Transactions on Biomedical Engineering* 58.3 (Mar. 2011), pp. 681–688. DOI: 10.1109/TBME.2010.2068298.

[146] Jiang, N., Muceli, S., Graimann, B., Farina, D., "Effect of Arm Position on the Prediction of Kinematics from EMG in Amputees". In: *Medical & Biological Engineering & Computing* 51.1 (Feb. 2013), pp. 143–151. DOI: 10.1007/s11517-012-0979-4.

[147] Muceli, S., Farina, D., "Simultaneous and Proportional Estimation of Hand Kinematics From EMG During Mirrored Movements at Multiple Degrees-of-Freedom". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 20.3 (May 2012), pp. 371–378. DOI: 10.1109/TNSRE.2011.2178039.

[148] Jiang, N., Vest-Nielsen, J. L. G., Muceli, S., Farina, D., "EMG-based Simultaneous and Proportional Estimation of Wrist/Hand Kinematics in Uni-Lateral Trans-Radial Amputees". In: *Journal of NeuroEngineering and Rehabilitation* 9.1 (June 2012), p. 42. DOI: 10.1186/1743-0003-9-42.

[149] Smith, L. H., Kuiken, T. A., Hargrove, L. J., "Use of Probabilistic Weights to Enhance Linear Regression Myoelectric Control". In: *Journal of Neural Engineering* 12.6 (Nov. 2015), p. 066030. DOI: 10.1088/1741-2560/12/6/066030.

[150] Piazza, C., Rossi, M., Catalano, M. G., Bicchi, A., Hargrove, L. J., "Evaluation of a Simultaneous Myoelectric Control Strategy for a Multi-DoF Transradial Prosthesis". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28.10 (Oct. 2020), pp. 2286–2295. DOI: 10.1109/TNSRE.2020.3016909.

[151] Muceli, S., Jiang, N., Farina, D., "Multichannel Surface EMG Based Estimation of Bilateral Hand Kinematics during Movements at Multiple Degrees of Freedom". In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology.* Aug. 2010, pp. 6066–6069. DOI: 10.1109/IEMBS.2010.5627622.

[152] Jiang, N., Vujaklija, I., Rehbaum, H., Graimann, B., Farina, D., "Is Accurate Mapping of EMG Signals on Kinematics Needed for Precise Online Myoelectric Control?" In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.3 (May 2014), pp. 549–558. DOI: 10.1109/TNSRE.2013.2287383.

[153] Hahne, J. M., Schweisfurth, M. A., Koppe, M., Farina, D., "Simultaneous Control of Multiple Functions of Bionic Hand Prostheses: Performance and Robustness in End Users". In: *Science Robotics* 3.19 (June 2018), eaat3630. DOI: 10.1126/scirobotics.aat3630.

[154] Vujaklija, I., Shalchyan, V., Kamavuako, E. N., Jiang, N., Marateb, H. R., Farina, D., "Online Mapping of EMG Signals into Kinematics by Autoencoding". In: *Journal of NeuroEngineering and Rehabilitation* 15.1 (Dec. 2018), p. 21. DOI: 10.1186/s12984-018-0363-1.

[155] Hagengruber, A., Leipscher, U., Eskofier, B. M., Vogel, J., "A New Labeling Approach for Proportional Electromyographic Control". In: *Sensors* 22.4 (Jan. 2022), p. 1368. DOI: 10.3390/s22041368.

[156] George, J. A., Brinton, M. R., Duncan, C. C., Hutchinson, D. T., Clark, G. A., "Improved Training Paradigms and Motor-decode Algorithms: Results from Intact Individuals and a Recent Transradial Amputee with Prior Complex Regional Pain Syndrome". In: *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* July 2018, pp. 3782–3787. DOI: 10.1109/EMBC.2018.8513342.

[157] George, J. A., Davis, T. S., Brinton, M. R., Clark, G. A., "Intuitive Neuromyoelectric Control of a Dexterous Bionic Arm Using a Modified Kalman Filter". In: *Journal of Neuroscience Methods* 330 (Jan. 2020), p. 108462. DOI: 10.1016/j.jneumeth.2019.108462.

[158] Roche, A. D., Rehbaum, H., Farina, D., Aszmann, O. C., "Prosthetic Myoelectric Control Strategies: A Clinical Perspective". In: *Current Surgery Reports* 2.3 (Jan. 2014), p. 44. DOI: 10.1007/s40137-013-0044-8.

[159] Cai, S., Lu, Z., Guo, L., Qing, Z., Yao, L., "The LET Procedure for Gesture Recognition With Multiple Forearm Angles". In: *IEEE Sensors Journal* 22.13 (July 2022), pp. 13226–13233. DOI: 10.1109/JSEN.2022.3177475.

[160] Amsüss, S., Vujaklija, I., Göbel, P., Roche, A. D., Graimann, B., Aszmann, O. C., Farina, D., “Context-Dependent Upper Limb Prosthesis Control for Natural and Robust Use”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 24.7 (July 2016), pp. 744–753. DOI: 10.1109/TNSRE.2015.2454240.

[161] Sherman, J., Morrison, W. J., “Adjustment of an Inverse Matrix Corresponding to a Change in One Element of a Given Matrix”. In: *The Annals of Mathematical Statistics* 21.1 (1950), pp. 124–127.

[162] de Oliveira, D. S., Ponfick, M., Braun, D. I., Osswald, M., Sierotowicz, M., Chatterjee, S., Weber, D., Eskofier, B. M., Castellini, C., Farina, D., Kinfe, T. M., Del Vecchio, A., *You Will Grasp Again: A Direct Spinal Cord/Computer Interface with the Spared Motor Neurons Restores the Dexterous Control of the Paralyzed Hand after Chronic Spinal Cord Injury.* Sept. 2022. DOI: 10.1101/2022.09.09.22279611.

[163] Rasouli, M., Ghosh, R., Wang Wei Lee, Thakor, N. V., Kukreja, S., “Stable Force-Myographic Control of a Prosthetic Hand Using Incremental Learning”. In: *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* Milan: IEEE, Aug. 2015, pp. 4828–4831. DOI: 10.1109/EMBC.2015.7319474.

[164] Hayes, M. H. *Statistical Digital Signal Processing and Modeling.* 1st. USA: John Wiley & Sons, Inc., 1996.

[165] Hahne, J. M., Dahne, S., Hwang, H.-J., Müller, K.-R., Parra, L. C., “Concurrent Adaptation of Human and Machine Improves Simultaneous and Proportional Myoelectric Control”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 23.4 (July 2015), pp. 618–627. DOI: 10.1109/TNSRE.2015.2401134.

[166] Yeung, D., Farina, D., Vujaklija, I., “Directional Forgetting for Stable Co-Adaptation in Myoelectric Control”. In: *Sensors* 19.9 (May 2019), p. 2203. DOI: 10.3390/s19092203.

[167] Kuiken, T. A., Miller, L. A., Turner, K. L., Hargrove, L. J., “A Comparison of Pattern Recognition Control and Direct Control of a Multiple Degree-of-Freedom Transradial Prosthesis”. In: *IEEE Journal of Translational Engineering in Health and Medicine* 4 (2016), pp. 1–8. DOI: 10.1109/JTEHM.2016.2616123.

[168] Jiang, N., Lorrain, T., Farina, D., “A State-Based, Proportional Myoelectric Control Method: Online Validation and Comparison with the Clinical State-of-the-Art”. In: *Journal of NeuroEngineering and Rehabilitation* 11.1 (2014), p. 110. DOI: 10.1186/1743-0003-11-110.

[169] Resnik, L., Huang, H. (, Winslow, A., Crouch, D. L., Zhang, F., Wolk, N., “Evaluation of EMG Pattern Recognition for Upper Limb Prosthesis Control: A Case Study in Comparison with Direct Myoelectric Control”. In: *Journal of NeuroEngineering and Rehabilitation* 15.1 (Mar. 2018), p. 23. DOI: 10.1186/s12984-018-0361-3.

[170] Powell, M. A., Thakor, N. V., "A Training Strategy for Learning Pattern Recognition Control for Myoelectric Prostheses:" in: *JPO Journal of Prosthetics and Orthotics* 25.1 (Jan. 2013), pp. 30–41. DOI: `10.1097/JPO.0b013e31827af7c1`.

[171] Hoerl, A. E., Kennard, R. W., "Ridge Regression: Biased Estimation for Nonorthogonal Problems". In: *Technometrics* 12.1 (Feb. 1970), pp. 55–67. DOI: `10.1080/00401706.1970.10488634`.

[172] Saunders, C., Gammerman, A., Vovk, V., "Ridge Regression Learning Algorithm in Dual Variables". In: (1998), p. 7.

[173] Rifkin, R., Yeo, G., Poggio, T., "Regularized Least-Squares Classification". In: (2003), p. 25.

[174] Rahimi, A., Recht, B., "Random Features for Large-Scale Kernel Machines". In: *Advances in neural information processing systems* (2008), pp. 1177–1184.

[175] Scheme, E. J., Englehart, K. B., "Training Strategies for Mitigating the Effect of Proportional Control on Classification in Pattern Recognition–Based Myoelectric Control:" in: *JPO Journal of Prosthetics and Orthotics* 25.2 (Apr. 2013), pp. 76–83. DOI: `10.1097/JPO.0b013e318289950b`.

[176] Dwivedi, A., Groll, H., Beckerle, P., "A Systematic Review of Sensor Fusion Methods Using Peripheral Bio-Signals for Human Intention Decoding". In: *Sensors* 22.17 (Jan. 2022), p. 6319. DOI: `10.3390/s22176319`.

[177] Zhou, H., Alici, G., "Non-Invasive Human-Machine Interface (HMI) Systems With Hybrid On-Body Sensors for Controlling Upper-Limb Prosthesis: A Review". In: *IEEE Sensors Journal* 22.11 (June 2022), pp. 10292–10307. DOI: `10.1109/JSEN.2022.3169492`.

[178] Herrera-Luna, I., Rechy-Ramirez, E. J., Rios-Figueroa, H. V., Marin-Hernandez, A., "Sensor Fusion Used in Applications for Hand Rehabilitation: A Systematic Review". In: *IEEE Sensors Journal* 19.10 (May 2019), pp. 3581–3592. DOI: `10.1109/JSEN.2019.2897083`.

[179] Jaquier, N., Connan, M., Castellini, C., Calinon, S., "Combining Electromyography and Tactile Myography to Improve Hand and Wrist Activity Detection in Prostheses". In: *Technologies* 5.4 (Dec. 2017), p. 64. DOI: `10.3390/technologies5040064`.

[180] Ke, A., Huang, J., Chen, L., Gao, Z., He, J., "An Ultra-Sensitive Modular Hybrid EMG–FMG Sensor with Floating Electrodes". In: *Sensors* 20.17 (Jan. 2020), p. 4775. DOI: `10.3390/s20174775`.

[181] Jiang, S., Gao, Q., Liu, H., Shull, P. B., "A Novel, Co-Located EMG-FMG-sensing Wearable Armband for Hand Gesture Recognition". In: *Sensors and Actuators A: Physical* 301 (Jan. 2020), p. 111738. DOI: `10.1016/j.sna.2019.111738`.

[182] Wu, J., Tian, Z., Sun, L., Estevez, L., Jafari, R., “Real-Time American Sign Language Recognition Using Wrist-Worn Motion and Surface EMG Sensors”. In: *2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*. June 2015, pp. 1–6. DOI: 10.1109/BSN.2015.7299393.

[183] Fang, J., Xu, B., Zhou, X., Qi, H., “Research on Gesture Recognition Based on sEMG and Inertial Sensor Fusion”. In: *2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*. Oct. 2018, pp. 1562–1567. DOI: 10.1109/IAEAC.2018.8577542.

[184] DelPreto, J., Salazar-Gomez, A. F., Gil, S., Hasani, R., Guenther, F. H., Rus, D., “Plug-and-Play Supervisory Control Using Muscle and Brain Signals for Real-Time Gesture and Error Detection”. In: *Autonomous Robots* 44.7 (Sept. 2020), pp. 1303–1322. DOI: 10.1007/s10514-020-09916-x.

[185] Yang, X., Yan, J., Liu, H., “Comparative Analysis of Wearable A-Mode Ultrasound and sEMG for Muscle-Computer Interface”. In: *IEEE Transactions on Biomedical Engineering* 67.9 (Sept. 2020), pp. 2434–2442. DOI: 10.1109/TBME.2019.2962499.

[186] Zeng, J., Zhou, Y., Yang, Y., Xu, Z., Zhang, H., Liu, H., “Robustness of Combined sEMG and Ultrasound Modalities Against Muscle Fatigue in Force Estimation”. In: *Intelligent Robotics and Applications*. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2021, pp. 213–221. DOI: 10.1007/978-3-030-89134-3_20.

[187] Xia, W., Zhou, Y., Yang, X., He, K., Liu, H., “Toward Portable Hybrid Surface Electromyography/A-Mode Ultrasound Sensing for Human–Machine Interface”. In: *IEEE Sensors Journal* 19.13 (July 2019), pp. 5219–5228. DOI: 10.1109/JSEN.2019.2903532.

[188] Gijsberts, A., Caputo, B., “Exploiting Accelerometers to Improve Movement Classification for Prosthetics”. In: *2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR)*. June 2013, pp. 1–5. DOI: 10.1109/ICORR.2013.6650476.

[189] Gijsberts, A., Atzori, M., Castellini, C., Müller, H., Caputo, B., “Movement Error Rate for Evaluation of Machine Learning Methods for sEMG-Based Hand Movement Classification”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.4 (July 2014), pp. 735–744. DOI: 10.1109/TNSRE.2014.2303394.

[190] Fougner, A., Scheme, E. J., Chan, A. D. C., Englehart, K. B., Stavdahl, Ø., “A Multi-Modal Approach for Hand Motion Classification Using Surface EMG and Accelerometers”. In: *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Boston, MA: IEEE, Aug. 2011, pp. 4247–4250. DOI: 10.1109/IEMBS.2011.6091054.

[191] Fougner, A., Scheme, E. J., Chan, A. D. C., Englehart, K. B., Stavdahl, Ø., "Resolving the Limb Position Effect in Myoelectric Pattern Recognition". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 19.6 (Dec. 2011), pp. 644–651. DOI: 10.1109/TNSRE.2011.2163529.

[192] Bao, T., Xie, S. Q., Yang, P., Zhou, P., Zhang, Z., "Towards Robust, Adaptive and Reliable Upper-limb Motion Estimation Using Machine Learning and Deep Learning–A Survey in Myoelectric Control". In: *IEEE Journal of Biomedical and Health Informatics* (2022), pp. 1–1. DOI: 10.1109/JBHI.2022.3159792.

[193] Connan, M., Sierotowicz, M., Henze, B., Porges, O., Albu-Schäffer, A., Roa, M. A., Castellini, C., "Learning to Teleoperate an Upper-Limb Assistive Humanoid Robot for Bimanual Daily-Living Tasks". In: *Biomedical Physics & Engineering Express* 8.1 (Dec. 2021), p. 015022. DOI: 10.1088/2057-1976/ac3881.

[194] Connan, M., Sierotowicz, M., Henze, B., Porges, O., Albu-Schäffer, A., Roa, M. A., Castellini, C., "Learning Teleoperation of an Assistive Humanoid Platform by Intact and Upper-Limb Disabled Users". In: *Converging Clinical and Engineering Research on Neurorehabilitation IV*. Biosystems & Biorobotics. Cham: Springer International Publishing, 2022, pp. 165–169. DOI: 10.1007/978-3-030-70316-5_27.

[195] de Vignemont, F. "Embodiment, Ownership and Disownership". In: *Consciousness and Cognition*. Brain and Self: Bridging the Gap 20.1 (Mar. 2011), pp. 82–93. DOI: 10.1016/j.concog.2010.09.004.

[196] Botvinick, M., Cohen, J., "Rubber Hands 'Feel' Touch That Eyes See". In: *Nature* 391.6669 (Feb. 1998), pp. 756–756. DOI: 10.1038/35784.

[197] Tyler, D. J. "Neural Interfaces for Somatosensory Feedback: Bringing Life to a Prosthesis". In: *Current Opinion in Neurology* 28.6 (Dec. 2015), pp. 574–581. DOI: 10.1097/WCO.0000000000000266.

[198] Erlenwein, J., Diers, M., Ernst, J., Schulz, F., Petzke, F., "Clinical Updates on Phantom Limb Pain". In: *Pain Reports* 6.1 (Jan. 2021). DOI: 10.1097/PR9.0000000000000888.

[199] Flor, H., Elbert, T., Knecht, S., Wienbruch, C., Pantev, C., Birbaumers, N., Larbig, W., Taub, E., "Phantom-Limb Pain as a Perceptual Correlate of Cortical Reorganization Following Arm Amputation". In: *Nature* 375.6531 (June 1995), pp. 482–484. DOI: 10.1038/375482a0.

[200] Flor, H., Birbaumer, N., "Phantom Limb Pain: Cortical Plasticity and Novel Therapeutic Approaches". In: *Current Opinion in Anesthesiology* 13.5 (Oct. 2000), pp. 561–564.

[201] Lotze, M., Grodd, W., Birbaumer, N., Erb, M., Huse, E., Flor, H., "Does Use of a Myoelectric Prosthesis Prevent Cortical Reorganization and Phantom Limb Pain?" In: *Nature Neuroscience* 2.6 (June 1999), pp. 501–502. DOI: 10.1038/9145.

[202] Sturma, A., Hruby, L., Vujaklija, I., Østlie, K., Farina, D., "Treatment Strategies for Phantom Limb Pain". In: *Bionic Limb Reconstruction*. Cham: Springer International Publishing, 2021, pp. 113–124. DOI: 10.1007/978-3-030-60746-3_12.

[203] Makin, T. R. "Phantom Limb Pain: Thinking Outside the (Mirror) Box". In: *Brain* 144.7 (July 2021), pp. 1929–1932. DOI: 10.1093/brain/awab139.

[204] Lenggenhager, B., Arnold, C. A., Giummarra, M. J., "Phantom Limbs: Pain, Embodiment, and Scientific Advances in Integrative Therapies". In: *WIREs Cognitive Science* 5.2 (2014), pp. 221–231. DOI: 10.1002/wcs.1277.

[205] Makin, T. R., de Vignemont, F., Faisal, A. A., "Neurocognitive Barriers to the Embodiment of Technology". In: *Nature Biomedical Engineering* 1.1 (Jan. 2017), pp. 1–3. DOI: 10.1038/s41551-016-0014.

[206] Nava, E., Röder, B., "Chapter 12 - Adaptation and Maladaptation: Insights from Brain Plasticity". In: *Progress in Brain Research*. Vol. 191. Enhancing Performance for Action and Perception. Elsevier, Jan. 2011, pp. 177–194. DOI: 10.1016/B978-0-444-53752-2.00005-9.

[207] Maimon Mor, R. O., Makin, T. R., "Is an Artificial Limb Embodied as a Hand? Brain Decoding in Prosthetic Limb Users". In: *PLOS Biology* 18.6 (June 2020), e3000729. DOI: 10.1371/journal.pbio.3000729.

[208] Beckerle, P., Castellini, C., Lenggenhager, B., Dosen, S., "Editorial: Embodiment and Co-adaptation Through Human-Machine Interfaces: At the Border of Robotics, Neuroscience and Psychology". In: *Frontiers in Neurorobotics* 16 (2022).

[209] von Glasersfeld, E. "Learning as a Constructive Activity". In: *Proceedings of the 5th Annual Meeting of the North American Group of Psychology in Mathematics Education, Vol. 1* (1983), pp. 41–101.

[210] von Glasersfeld, E. *Radical Constructivism: A Way of Knowing and Learning.* Falmer Press, London, 1995.

[211] Bishop, C. M. *Pattern Recognition and Machine Learning.* Vol. 4. Information Science and Statistics. Springer New York, NY, 2006.

[212] Sarkar, A. "Constructivist Design for Interactive Machine Learning". In: *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems.* CHI EA '16. New York, NY, USA: Association for Computing Machinery, May 2016, pp. 1467–1475. DOI: 10.1145/2851581.2892547.

[213] Atzori, M., Gijsberts, A., Castellini, C., Caputo, B., Mittaz Hager, A.-G., Elsig, S., Giatsidis, G., Bassetto, F., Müller, H., "Electromyography Data for Non-Invasive Naturally-Controlled Robotic Hand Prostheses". In: *Scientific Data* 1.1 (Dec. 2014), p. 140053. DOI: 10.1038/sdata.2014.53.

[214] Hargrove, L. J., Losier, Y. G., Lock, B. A., Englehart, K. B., Hudgins, B. S., "A Real-Time Pattern Recognition Based Myoelectric Control Usability Study Implemented in a Virtual Environment". In: *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Aug. 2007, pp. 4842–4845. DOI: 10.1109/IEMBS.2007.4353424.

[215] Ortiz-Catalan, M., Rouhani, F., Brånemark, R., Håkansson, B., "Offline Accuracy: A Potentially Misleading Metric in Myoelectric Pattern Recognition for Prosthetic Control". In: *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Milan: IEEE, Aug. 2015, pp. 1140–1143. DOI: 10.1109/EMBC.2015.7318567.

[216] Kristoffersen, M. B., Franzke, A. W., van der Sluis, C. K., Murgia, A., Bongers, R. M., "The Effect of Feedback During Training Sessions on Learning Pattern-Recognition-Based Prosthesis Control". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 27.10 (Oct. 2019), pp. 2087–2096. DOI: 10.1109/TNSRE.2019.2929917.

[217] Nawfel, J. L., Englehart, K. B., Scheme, E. J., "A Multi-Variate Approach to Predicting Myoelectric Control Usability". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 29 (2021), pp. 1312–1327. DOI: 10.1109/TNSRE.2021.3094324.

[218] Simon, A. M., Hargrove, L. J., Lock, B. A., Kuiken, T. A., "The Target Achievement Control Test: Evaluating Real-Time Myoelectric Pattern-Recognition Control of Multifunctional Upper-Limb Prostheses". In: *The Journal of Rehabilitation Research and Development* 48.6 (2011), p. 619. DOI: 10.1682/JRRD.2010.08.0149.

[219] Li, G., Schultz, A. E., Kuiken, T. A., "Quantifying Pattern Recognition—Based Myoelectric Control of Multifunctional Transradial Prostheses". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 18.2 (Apr. 2010), pp. 185–192. DOI: 10.1109/TNSRE.2009.2039619.

[220] Ortiz-Catalan, M., Håkansson, B., Brånemark, R., "Real-Time Classification of Simultaneous Hand and Wrist Motions Using Artificial Neural Networks with Variable Threshold Outputs". In: (2013), p. 7.

[221] Ortiz-Catalan, M., Håkansson, B., Brånemark, R., "Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.4 (July 2014), pp. 756–764. DOI: 10.1109/TNSRE.2014.2305097.

[222] Williams, M. R., Kirsch, R. F., "Evaluation of Head Orientation and Neck Muscle EMG Signals as Command Inputs to a Human–Computer Interface for Individuals With High Tetraplegia". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 16.5 (Oct. 2008), pp. 485–496. DOI: 10.1109/TNSRE.2008.2006216.

[223] Fitts, P. M. "The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement". In: *Journal of Experimental Psychology* 47 (1954), pp. 381–391. DOI: 10.1037/h0055392.

[224] Kyberd, P. J. "Outcome Measures". In: *Bionic Limb Reconstruction*. Cham: Springer International Publishing, 2021, pp. 57–74.

[225] Hermansson, L., Fisher, A., Bernspång, B., Eliasson, A.-C., "Assessment of Capacity for Myoelectric Control: A New Rasch-Built Measure of Prosthetic Hand Control". In: *Journal of Rehabilitation Medicine* -1.1 (Jan. 2004), pp. 1–1. DOI: 10.1080/16501970410024280.

[226] Light, C. M., Chappell, P. H., Kyberd, P. J., "Establishing a Standardized Clinical Assessment Tool of Pathologic and Prosthetic Hand Function: Normative Data, Reliability, and Validity". In: *Archives of Physical Medicine and Rehabilitation* 83.6 (June 2002), pp. 776–783. DOI: 10.1053/apmr.2002.32737.

[227] Kyberd, P. J., Hussaini, A., Maillet, G., "Characterisation of the Clothespin Relocation Test as a Functional Assessment Tool". In: *Journal of Rehabilitation and Assistive Technologies Engineering* 5 (Jan. 2018), p. 2055668317750810. DOI: 10.1177/2055668317750810.

[228] Desrosiers, J., Bravo, G., Hébert, R., Dutil, É., Mercier, L., "Validation of the Box and Block Test as a Measure of Dexterity of Elderly People: Reliability, Validity, and Norms Studies". In: *Archives of Physical Medicine and Rehabilitation* 75.7 (July 1994), pp. 751–755. DOI: 10.1016/0003-9993(94)90130-9.

[229] Hebert, J. S., Lewicke, J., "Case Report of Modified Box and Blocks Test with Motion Capture to Measure Prosthetic Function". In: *Journal of Rehabilitation Research and Development* 49.8 (2012), pp. 1163–1174. DOI: 10.1682/jrrd.2011.10.0207.

[230] *CRediT*. https://credit.niso.org/. (accessed 2023-02-09).

[231] Dietterichl, T. G. "Ensemble Learning". In: *The Handbook of Brain Theory and Neural Networks*. MIT Press, 2002, pp. 405–408.

[232] Belyea, A., Englehart, K. B., Scheme, E. J., "FMG Versus EMG: A Comparison of Usability for Real-Time Pattern Recognition Based Control". In: *IEEE Transactions on Biomedical Engineering* 66.11 (Nov. 2019), pp. 3098–3104. DOI: 10.1109/TBME.2019.2900415.

[233] Hargrove, L. J., Englehart, K. B., Hudgins, B. S., "A Comparison of Surface and Intramuscular Myoelectric Signal Classification". In: *IEEE Transactions on Biomedical Engineering* 54.5 (May 2007), pp. 847–853. DOI: 10.1109/TBME.2006.889192.

[234] Ison, M., Vujaklija, I., Whitsell, B., Farina, D., Artemiadis, P. K., "High-Density Electromyography and Motor Skill Learning for Robust Long-Term Control of a 7-DoF Robot Arm". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 24.4 (Apr. 2016), pp. 424–433. DOI: 10.1109/TNSRE.2015.2417775.

[235] Smith, L. H., Kuiken, T. A., Hargrove, L. J., “Evaluation of Linear Regression Simultaneous Myoelectric Control Using Intramuscular EMG”. In: *IEEE Transactions on Biomedical Engineering* 63.4 (Apr. 2016), pp. 737–746. DOI: 10.1109/TBME.2015.2469741.

[236] Amma, C., Krings, T., Böer, J., Schultz, T., “Advancing Muscle-Computer Interfaces with High-Density Electromyography”. In: *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. CHI ’15. New York, NY, USA: Association for Computing Machinery, Apr. 2015, pp. 929–938. DOI: 10.1145/2702123.2702501.

[237] Rojas-Martínez, M., Mañanas, M. A., Alonso, J. F., Merletti, R., “Identification of Isometric Contractions Based on High Density EMG Maps”. In: *Journal of Electromyography and Kinesiology* 23.1 (Feb. 2013), pp. 33–42. DOI: 10.1016/j.jelekin.2012.06.009.

[238] Barsotti, M., Dupan, S., Vujaklija, I., Došen, S., Frisoli, A., Farina, D., “Online Finger Control Using High-Density EMG and Minimal Training Data for Robotic Applications”. In: *IEEE Robotics and Automation Letters* 4.2 (Apr. 2019), pp. 217–223. DOI: 10.1109/LRA.2018.2885753.

[239] Vidovic, M. M.-C., Hwang, H.-J., Amsüss, S., Hahne, J. M., Farina, D., Müller, K.-R., “Improving the Robustness of Myoelectric Pattern Recognition for Upper Limb Prostheses by Covariate Shift Adaptation”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 24.9 (Sept. 2016), pp. 961–970. DOI: 10.1109/TNSRE.2015.2492619.

[240] Prahm, C., Schulz, A., Paaßen, B., Schoisswohl, J., Kaniusas, E., Dorffner, G., Hammer, B., Aszmann, O. C., “Counteracting Electrode Shifts in Upper-Limb Prosthesis Control via Transfer Learning”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 27.5 (May 2019), pp. 956–962. DOI: 10.1109/TNSRE.2019.2907200.

[241] Fukuda, O., Tsuji, T., Kaneko, M., Otsuka, A., “A Human-Assisting Manipulator Teleoperated by EMG Signals and Arm Motions”. In: *IEEE Transactions on Robotics and Automation* 19.2 (Apr. 2003), pp. 210–222. DOI: 10.1109/TRA.2003.808873.

[242] Sensinger, J. W., Lock, B. A., Kuiken, T. A., “Adaptive Pattern Recognition of Myoelectric Signals: Exploration of Conceptual Framework and Practical Algorithms”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 17.3 (June 2009), pp. 270–278. DOI: 10.1109/TNSRE.2009.2023282.

[243] Igual, C., Igual, J., Hahne, J. M., Parra, L. C., “Adaptive Auto-Regressive Proportional Myoelectric Control”. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 27.2 (Feb. 2019), pp. 314–322. DOI: 10.1109/TNSRE.2019.2894464.

[244] Bettoni, M. C., Castellini, C., "Interaction in Assistive Robotics: A Radical Constructivist Design Framework". In: *Frontiers in Neurorobotics* 15 (2021). DOI: 10.3389/fnbot.2021.675657.

[245] Vujaklija, I., Roche, A. D., Hasenoehrl, T., Sturma, A., Amsüss, S., Farina, D., Aszmann, O. C., "Translating Research on Myoelectric Control into Clinics—Are the Performance Assessment Methods Adequate?" In: *Frontiers in Neurorobotics* 11 (Feb. 2017). DOI: 10.3389/fnbot.2017.00007.

[246] Atkins, D. J., Sturma, A., "Principles of Occupational and Physical Therapy in Upper Limb Amputations". In: *Bionic Limb Reconstruction*. Cham: Springer International Publishing, 2021, pp. 197–214.

[247] Simon, A. M., Lock, B. A., Stubblefield, K. A., "Patient Training for Functional Use of Pattern Recognition–Controlled Prostheses". In: *JPO: Journal of Prosthetics and Orthotics* 24.2 (Apr. 2012), pp. 56–64. DOI: 10.1097/JPO.0b013e3182515437.

[248] Simon, A. M., Turner, K. L., Miller, L. A., Hargrove, L. J., Kuiken, T. A., "Pattern Recognition and Direct Control Home Use of a Multi-Articulating Hand Prosthesis". In: *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*. June 2019, pp. 386–391. DOI: 10.1109/ICORR.2019.8779539.

[249] Roche, A. D., Vujaklija, I., Amsüss, S., Sturma, A., Göbel, P., Farina, D., Aszmann, O. C., "A Structured Rehabilitation Protocol for Improved Multifunctional Prosthetic Control: A Case Study". In: *Journal of Visualized Experiments : JoVE* 105 (Nov. 2015). DOI: 10.3791/52968.

[250] Cusack, W., Cope, M., Nathanson, S., Pirouz, N., Kistenberg, R., Wheaton, L., "Neural Activation Differences in Amputees during Imitation of Intact versus Amputee Movements". In: *Frontiers in Human Neuroscience* 6 (2012).

[251] Hargrove, L. J., Miller, L. A., Turner, K. L., Kuiken, T. A., "Myoelectric Pattern Recognition Outperforms Direct Control for Transhumeral Amputees with Targeted Muscle Reinnervation: A Randomized Clinical Trial". In: *Scientific Reports* 7.1 (Oct. 2017), p. 13840. DOI: 10.1038/s41598-017-14386-w.

[252] Segil, J. L., Huddle, S. A., Weir, R. F., "Functional Assessment of a Myoelectric Postural Controller and Multi-Functional Prosthetic Hand by Persons With Trans-Radial Limb Loss". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 25.6 (June 2017), pp. 618–627. DOI: 10.1109/TNSRE.2016.2586846.

[253] Waris, A., Niazi, I. K., Jamil, M., Englehart, K. B., Jensen, W., Kamavuako, E. N., "Multiday Evaluation of Techniques for EMG-Based Classification of Hand Motions". In: *IEEE Journal of Biomedical and Health Informatics* 23.4 (July 2019), pp. 1526–1534. DOI: 10.1109/JBHI.2018.2864335.

[254] OT Bioelettronica s.r.l. *MuoviPro*. https://www.otbioelettronica.it/en/products/hardware/muovipro. (accessed 2023-01-09).

[255] OT Bioelettronica s.r.l. *Muovi+Pro*. `https://www.otbioelettronica.it/en/products/hardware/muovi-pro`. (accessed 2023-01-09).

[256] Farina, D., Vujaklija, I., Sartori, M., Kapelner, T., Negro, F., Jiang, N., Bergmeister, K., Andalib, A., Principe, J., Aszmann, O. C., "Man/Machine Interface Based on the Discharge Timings of Spinal Motor Neurons after Targeted Muscle Reinnervation". In: *Nature Biomedical Engineering* 1.2 (Feb. 2017), p. 0025. DOI: `10.1038/s41551-016-0025`.

[257] Sartori, M., Durandau, G., Došen, S., Farina, D., "Robust Simultaneous Myoelectric Control of Multiple Degrees of Freedom in Wrist-Hand Prostheses by Real-Time Neuromusculoskeletal Modeling". In: *Journal of Neural Engineering* 15.6 (Oct. 2018), p. 066026. DOI: `10.1088/1741-2552/aae26b`.

[258] Kapelner, T., Sartori, M., Negro, F., Farina, D., "Neuro-Musculoskeletal Mapping for Man-Machine Interfacing". In: *Scientific Reports* 10.1 (Dec. 2020), p. 5834. DOI: `10.1038/s41598-020-62773-7`.

[259] Holzbaur, K. R. S., Murray, W. M., Delp, S. L., "A Model of the Upper Extremity for Simulating Musculoskeletal Surgery and Analyzing Neuromuscular Control". In: *Annals of Biomedical Engineering* 33.6 (June 2005), pp. 829–840. DOI: `10.1007/s10439-005-3320-7`.

[260] Saul, K. R., Hu, X., Goehler, C. M., Vidt, M. E., Daly, M., Velisar, A., Murray, W. M., "Benchmarking of Dynamic Simulation Predictions in Two Software Platforms Using an Upper Limb Musculoskeletal Model". In: *Computer Methods in Biomechanics and Biomedical Engineering* 18.13 (Oct. 2015), pp. 1445–1458. DOI: `10.1080/10255842.2014.916698`.

[261] Delp, S. L., Anderson, F. C., Arnold, A. S., Loan, P., Habib, A., John, C. T., Guendelman, E., Thelen, D. G., "OpenSim: Open-Source Software to Create and Analyze Dynamic Simulations of Movement". In: *IEEE Transactions on Biomedical Engineering* 54.11 (Nov. 2007), pp. 1940–1950. DOI: `10.1109/TBME.2007.901024`.

[262] Zajac, F. E. "Muscle and Tendon: Properties, Models, Scaling, and Application to Biomechanics and Motor Control". In: *Critical reviews in biomedical engineering* 17.4 (Jan. 1989), pp. 359–411.

[263] Damsgaard, M., Rasmussen, J., Christensen, S. T., Surma, E., de Zee, M., "Analysis of Musculoskeletal Systems in the AnyBody Modeling System". In: *Simulation Modelling Practice and Theory.* SIMS 2004 14.8 (Nov. 2006), pp. 1100–1111. DOI: `10.1016/j.simpat.2006.09.001`.

[264] Glaser, V., Holobar, A., Zazula, D., "Real-Time Motor Unit Identification From High-Density Surface EMG". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 21.6 (Nov. 2013), pp. 949–958. DOI: `10.1109/TNSRE.2013.2247631`.

[265] Barsakcioglu, D. Y., Bracklein, M., Holobar, A., Farina, D., “Control of Spinal Motoneurons by Feedback From a Non-Invasive Real-Time Interface”. In: *IEEE Transactions on Biomedical Engineering* 68.3 (Mar. 2021), pp. 926–935. DOI: 10.1109/TBME.2020.3001942.

[266] Shirzadi, M., Marateb, H. R., McGill, K. C., Muceli, S., Mananas, M. A., Farina, D., “An Accurate and Real-time Method for Resolving Superimposed Action Potentials in MultiUnit Recordings”. In: *IEEE Transactions on Biomedical Engineering* (2022), pp. 1–12. DOI: 10.1109/TBME.2022.3192119.

[267] Gigli, A., Gijsberts, A., Castellini, C., “Unsupervised Myocontrol of a Virtual Hand Based on a Coadaptive Abstract Motor Mapping”. In: *2022 International Conference on Rehabilitation Robotics (ICORR)*. July 2022, pp. 1–6. DOI: 10.1109/ICORR55369.2022.9896414.

[268] Yeung, D., Mendez Guerra, I., Barner-Rasmussen, I., Siponen, E., Farina, D., Vujaklija, I., “Co-Adaptive Control of Bionic Limbs via Unsupervised Adaptation of Muscle Synergies”. In: *IEEE Transactions on Biomedical Engineering* (2022), pp. 1–1. DOI: 10.1109/TBME.2022.3150665.

[269] Cipriani, C., Zaccone, F., Micera, S., Carrozza, M. C., “On the Shared Control of an EMG-Controlled Prosthetic Hand: Analysis of User–Prosthesis Interaction”. In: *IEEE Transactions on Robotics* 24.1 (Feb. 2008), pp. 170–184. DOI: 10.1109/TRO.2007.910708.

[270] Seppich, N., Tacca, N., Chao, K.-Y., Akim, M., Hidalgo-Carvajal, D., Pozo Fortunić, E., Tödtheide, A., Kühn, J., Haddadin, S., “CyberLimb: A Novel Robotic Prosthesis Concept with Shared and Intuitive Control”. In: *Journal of NeuroEngineering and Rehabilitation* 19.1 (Apr. 2022), p. 41. DOI: 10.1186/s12984-022-01016-4.

[271] Artemiadis, P. K., Kyriakopoulos, K. J., “An EMG-Based Robot Control Scheme Robust to Time-Varying EMG Signal Features”. In: *IEEE Transactions on Information Technology in Biomedicine* 14.3 (May 2010), pp. 582–588. DOI: 10.1109/TITB.2010.2040832.

[272] Ajoudani, A., Zanchettin, A. M., Ivaldi, S., Albu-Schäffer, A., Kosuge, K., Khatib, O., “Progress and Prospects of the Human–Robot Collaboration”. In: *Autonomous Robots* 42.5 (June 2018), pp. 957–975. DOI: 10.1007/s10514-017-9677-2.

[273] Colgate, J. E., Wannasuphoprasit, W., Peshkin, M. A., “Cobots: Proceedings of the 1996 ASME International Mechanical Engineering Congress and Exposition”. In: Dec. 1996, pp. 433–439.

[274] Villani, V., Pini, F., Leali, F., Secchi, C., “Survey on Human–Robot Collaboration in Industrial Settings: Safety, Intuitive Interfaces and Applications”. In: *Mechatronics* 55 (Nov. 2018), pp. 248–266. DOI: 10.1016/j.mechatronics.2018.02.009.

[275] Franzel, F., Eiband, T., Lee, D., "Detection of Collaboration and Collision Events during Contact Task Execution". In: *2020 IEEE-RAS 20th International Conference on Humanoid Robots (Humanoids)*. July 2021, pp. 376–383. DOI: 10.1109/HUMANOIDS47582.2021.9555677.

[276] Eiband, T., Willibald, C., Tannert, I., Weber, B. M., Lee, D., "Collaborative Programming of Robotic Task Decisions and Recovery Behaviors". In: *Autonomous Robots* (Oct. 2022). DOI: 10.1007/s10514-022-10062-9.

[277] Kuiken, T. A. "Targeted Reinnervation for Improved Prosthetic Function". In: *Physical Medicine and Rehabilitation Clinics of North America*. New Advances in Prosthetics and Orthotics 17.1 (Feb. 2006), pp. 1–13. DOI: 10.1016/j.pmr.2005.10.001.

A Full Text Publications

This chapter contains all full text publications that contributed to this dissertation with information about the *authors*, the *medium of publication*, the *copyright*, and a *citation notice*.

Publication 1 Action Interference in Simultaneous and Proportional Myocontrol: Comparing Force- and Electromyography

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Action Interference in Simultaneous and Proportional Myocontrol: Comparing Force- and Electromyography

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Abstract.

Myocontrol, that is, control of a prosthesis via muscle signals, is still a surprisingly hard problem. Recent research indicates that surface electromyography (sEMG), the traditional technique used to detect a subject's intent, could proficiently be replaced, or conjoined with, other techniques (multi-modal myocontrol), with the aim to improve both on dexterity and reliability. In this paper we present an online assessment of multi-modal sEMG and force myography (FMG) targeted at hand and wrist myocontrol. Twenty sEMG and FMG sensors in total were used to enforce simultaneous and proportional control of hand opening/closing, wrist pronation/supination and wrist flexion/extension of 12 intact subjects. We found that FMG yields in general a better performance than sEMG, and that the main drawback of the sEMG array we used is not the inability to perform a desired action, but rather *action interference*, that is, the undesired concurrent activation of another action. FMG, on the other hand, causes less interference.

Keywords: myocontrol, surface electromyography, force myography, prosthetics, target achievement control, action interference

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1. Introduction

Smooth, natural control of upper-limb prostheses (an instance of *myocontrol*) is the typical problem which looks simple from an abstract point of view and turns out to be extremely hard in practice. Back in the Fifties surface electromyography (sEMG), formerly a musculoskeletal condition diagnostic technique, began to be used in a two-sensors configuration to open and close a one-degree-of-freedom (DOF) motorized gripper — actually, the first self-powered hand prosthesis in history. Surprisingly, this rudimentary form of control is, still today, unsurpassed in practice, although (multi-sensor) sEMG was targeted by control theorists and mathematicians soon after the pioneers' era (an early example can be found in [11]).

Yet, dexterous myocontrol, e.g., control of multi-DOF self-powered prosthetic hands and wrists, is still by and large unsolved, the main problem being unreliability in daily-life activities. On top of this, upper-limb prosthetic hardware is still expensive, heavy and clumsy: these are the main reasons why self-powered prostheses are so often rejected [12, 23], although better functionality and control are highly desired characteristics in the population of patients [6, 8]. Only two commercially available solutions employing machine learning are known, namely *Complete control* by COAPT Engineerings and the *Myo Plus* by Ottobock. Proper myocontrol is a surprisingly hard problem and fifty years of research have not yet produced a reliable, dexterous, natural and clinically accepted system, enabling upper-limb amputees to smoothly control their prostheses [2].

Specifically, if we consider the human-machine interface devoted to enforcing myocontrol, *multi-modal sensing* is one of the solutions the community is attempting [9, 12, 15]. The idea is to gather more information from the surface of the amputee's missing limb than sEMG currently can, by using different kinds of sensors as a substitute of, or as a companion to, sEMG. Novel sensor modalities are being explored, which could yield information less prone to the well-known problems of sEMG (sweat, muscle fatigue, variability of the signal during isometric contractions due to motor unit recruitment); as well, they should be targeted at gathering information which sEMG cannot in principle provide such as, e.g., the status of deep muscles [3].

In this paper we focus upon one such alternative technique, force myography (FMG). As opposed to sEMG, which directly detects the electrical fields generated by muscle contractions, FMG uses pressure sensors placed on a body part of interest to interpret the deformations induced on the stump by said contractions. While contracting, muscles bulge and change the shape of, for instance, the forearm, in ways that can be quite reliably be associated to the actions enforced by the human wrist and hand [24]. FMG has potential to detect different information with respect to sEMG [26], provides similar accuracy and better-conditioned signals than sEMG [5, 32] and has already been tested offline and online even on amputees [4]; but as far as we know, studies on the *combination* of FMG and sEMG while in action are still scarce (a remarkable example being, e.g., [1]).

Building on our own previous work, in this paper we report about an experiment in which several intact subjects were fitted with twenty sEMG and FMG sensors on the forearm; they were then engaged in a repetitive *online* goal-reaching task involving the opening/closing of the hand, flexion/extension and pronation/supination of the wrist — an instance of the Target Achievement Control (TAC) test [28]. It is worthwhile to stress that the task was online, although still in controlled conditions (i.e., not in a daily-living-activity setup), since offline performance can only offer limited information of online performance in myocontrol [14, 21, 30]. The results of our experiment indicate that for proportional control, particularly for fine movements, requiring low forces, sEMG does not suffice and is outperformed by FMG. The shortcoming can be traced back to the unintended activation of an action, when trying to perform a different action, a phenomenon we call *action interference*.

1.1. Related work

Surface EMG [16,17] detects a superposition of many Motor Unit Activation Potentials, filtered by the tissue the signal travels through. These signals are, electrical fields generated by motor units during muscle contraction. FMG [24, 31], on the other side, detects the pressure exerted by the muscles towards the surface of the skin by volumetric changes induced during muscle activity. Due to the very different nature of the signals gathered by these two techniques, it seems reasonable that they could be proficiently fused in order to better detect a subject's intent.

In particular, FMG alone has already been tested by and large, and has proved to yield a signal which is more resilient to motion artefacts and fatigue than sEMG [32], and has been directly applied to amputees: in [4] four amputated subjects were able to enforce six primary grips through classification, with an accuracy of above 70%. On the other hand, FMG and sEMG have been comparatively examined but in parallel, i.e., without combining them, in [5, 26]. The results shown therein indicate that FMG provides a signal which is less oscillatory during isometric contractions than sEMG, thereby providing a significantly better performance during intent detection, performed using a regression approach, i.e., without classification of patterns but rather enforcing simultaneous and proportional control.

To the best of our knowledge, this study represents the first attempt to mix sEMG and FMG in an online task, with the aim of determining *how to best combine* the two techniques. In our own previous work [20], an *offline* analysis was performed of data obtained in conditions similar to the ones we report about here. The results therein showed that (a) it is not important how the sensors are laid out on the forearm, but (b) it can make a significant difference how the signals are combined. In particular, four ML approaches were tested, and it was determined that sEMG alone performed significantly worse than any other approach (i.e., FMG alone or combined with sEMG in two different ways). Moreover, quite surprisingly, it was determined that the best way of combining the two techniques consisted of just feeding to the ML system the sEMG and FMG signals juxtaposed. This approach led to smaller normalised root-mean-squared error in the offline analysis, as well as to better success ratio and shorter task completion times in a preliminary online test, performed on one subject only. This very work can be therefore viewed as the natural companion and completion of the above-mentioned paper.

2. Materials and Methods

As an extension of [20], where the comparison was performed mostly offline (only a single user online test), this study involved 12 able-bodied subjects in a completely online goal-reaching scenario — an instance of the Target Achievement Control test [28]. Furthermore, the design of this study allows an in-depth comparison of the approaches for different types of goals that the subjects had to reach. These goals differ as far as the *action* (the hand gesture) that had to be performed is concerned, as well as regarding the *level of activation*, the intensity / force to which the action had to be performed. An example would be *wrist flexion* at *level 0.33*. Here the subjects would need to flex their wrist to 33% of full flexion to reach the goal.‡ Notice that, in this work, we have intentionally left out the problem of predicting combined actions (e.g., grasping while pronating the wrist) since it would have led to too complex an experimental protocol, and it would probably have failed due to the small number of sensors.

2.1. Participants

We engaged 12 able-bodied subjects in our study (three women, nine men; age between 22 and 45; all but one right handed). Prior to the experiment all participants received written and oral descriptions of the experiment. After all questions about the experiments and associated risks were answered, all participants signed an informed consent form. This study was formally approved by the host institution's internal committee for data protection and it followed the guidelines of the World Medical Association's declaration of Helsinki.

2.2. Experimental Setup

The participant was comfortably seated in front of a computer screen and asked to wear a sEMG and FMG acquisition device that consists of two separate bracelets. A depiction of the full setup and the bracelet can be found in Figure 1.

The ten sEMG and ten FMG sensors were arranged in alternating order on the bracelets to cover the full circumference of the forearm by both the sEMG and FMG sensors. The influence of different sensors arrangements has already been investigated in [20] and no significant influence of the different sensor selections has been found. Therefore, we were not required to change the bracelet placement and sensor organisation for each of the four configurations we intended to compare.

On the screen the participants were shown two hand models, see the left image of Figure 1. Each of these hands serves a particular purpose. The left/grey hand serves as a stimulus to the participant. During the data acquisition or ML training, it indicates to the user which hand action to perform. During the goal-reaching part of the experiment, it indicates the target hand position the participant has to reach. The right/beige hand

‡ The percentage is related to a level set by the subject. The experimenter asked the subject to perform a tense, but comfortable level of force.

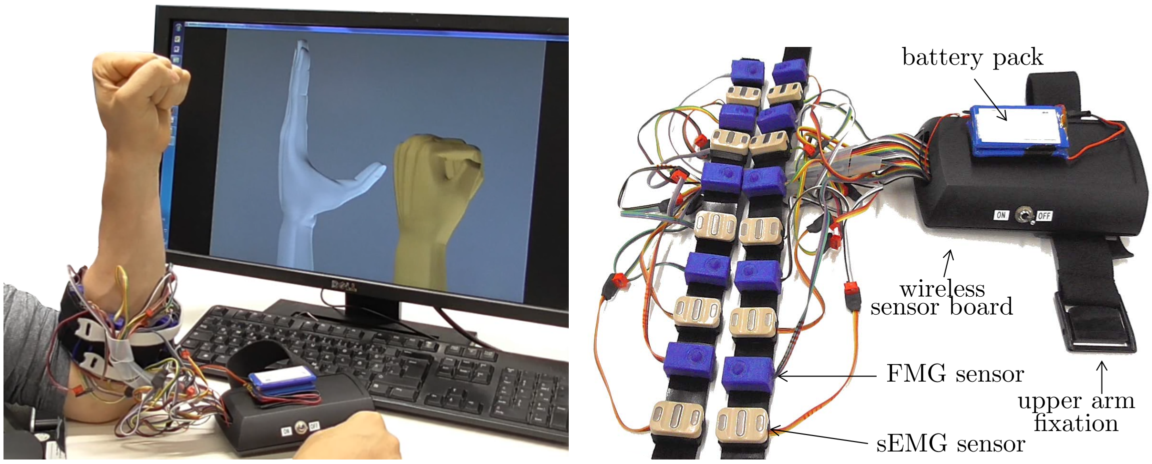

Figure 1: (left) the forearm of a participant wearing the sensors, the wireless data acquisition device, and the computer screen showing a target hand configuration (grey hand) and the current prediction of the ML algorithm (beige hand). (right) The wireless data acquisition device, consisting of a battery powered analog-digital converted and two bracelets with sEMG and FMG sensors.

is controlled by the user. It displays the prediction of the ML configuration that is currently in use. It is only active in the goal-reaching part of the experiment. With this setup the goal reaching becomes a matching task of left and right hand.

2.3. Hardware and Signal Processing

The sEMG electrodes are of type *Ottobock 13E200=50 Myobock* with internal filtering electronics, supplying an amplified, rectified and band-pass filtered sEMG signal. This sensor type has been designed for clinical applications. Explicit details about internal electronics and filters are not publicly available. The FMG sensors and its electronics are custom made and described in more detail in [5]. Basically, voltage over a force-sensing resistor (FSR) is amplified and then digitized. The FSR is embedded in a flexible 3D-printed housing. The sampling rate of both sEMG and FMG sensors is 100 Hz. Signals of both types have been filtered on the software side, using a 1st-order Butterworth low-pass filter with a cut-off frequency of 1 Hz. The output after the filtering stage is directly used for training and prediction.

2.4. Experimental Protocol

The experiment consists of two major parts. First, labelled muscle activation data is gathered from the participant, which is used to train a ML algorithm in four different signal mixing configurations. The underlying ML method is always the same. The difference lies in the sensors selection as well as in the modality of mixing the two sensor types. Furthermore, depending on what sensor type is used a hyperparameter is varied.

The four ML configurations are the same as in the offline analysis performed in [20], therefore the hyperparameters have been taken from that analysis.

The ML algorithm that we used is the well established *Ridge Regression with Random Fourier Features* (RRRFF), first introduced in prosthetic control in [13] and successfully used by this group numerous times [18,19,22,29]. This algorithm can be seen as a finite dimensional approximation of a *Support Vector Machine* (SVM) using a Radial Basis Function Kernel. This algorithm has certain in our opinion highly important characteristics, e.g. bounded in space and therefore fast computation, incrementality, and proportionality.

The central point of this work is an in-depth comparison between sEMG, FMG and the mixture of both. For this purpose we compared four configurations of training our ML algorithm, based on i.e. sEMG only, FMG only, a *stacked* mixture of both (STA) and a hierarchical mixture of both (ENS). The hierarchical configuration will be referred to as *ensemble learning* [7].

For the RRRFF algorithm, there is a target signal for each of the actions to be trained. These target values represent the hand/wrist configuration for the specific action. For the ENS model, a set of target signals is obtained from each, sEMG and FMG models. These target values correspond to the target values from the sEMG and FMG models, which are the predicted finger/hand configurations. Then a third model is trained with the stacked output of the first two models. From that third model, the final target values are obtained.

A visualisation of all four mixing configurations can be found in Figure 2.

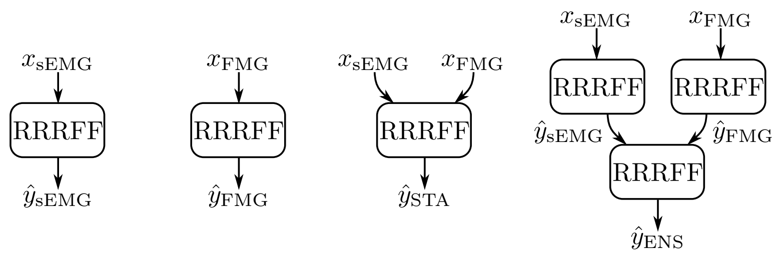

Figure 2: Visual representation of the four different ML configurations investigated in this work. From left to right: sEMG only, FMG only, stacked mixing (STA) and ensemble learning (ENS). This is a supplement to the description in Section 2.4.

To guarantee a fair comparison between these four configurations we always used a subset of ten sensors to test each configuration. This means we used all ten of the respective sensors, when we trained the ML algorithm for one specific sensor type only, but reduced the number of each sensor type to five, when training a mixing approach. Following this chain of thought, we were able to acquire training data once from all 20 sensors and train all four ML configurations with a subset of this data. This effectively reduced the duration of the experiment, easing the participants' task. Following the stimulus (grey hand model) the participant had to perform six different hand and wrist actions, namely rest or relaxed (no action), power grasp, wrist flexion, wrist extension, wrist pronation and wrist supination. A depiction of these actions can be found in Figure 3.

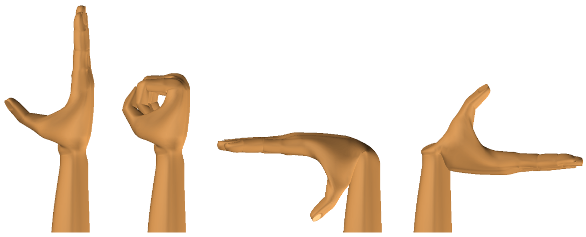

Figure 3: Depiction of the six actions the participants had to perform during the ML training phase.

These six actions were repeated 5 times. After the data acquisition and the subsequent ML training the participant was allowed to quickly test the quality of the online prediction performing free movements and comparing them to the predicted actions. In case the participants verbally stated that they are not satisfied the training session was repeated until the participants were satisfied with the performance. Thereafter the participants were presented with 120 goal reaching tasks. This segment of the experiment lasted on average $29'50'' \pm 3'20''$. The distinctive feature of these tasks is the fact that we train only on "on/off"-data, i.e. full activation of a particular action, but the goals can be intermediate values for these actions (a realistic training method already defined in [27]). Figure 4 depicts different levels for the actions wrist flexion and wrist extension. No updates or retraining were allowed once the first goal was presented to the participants.

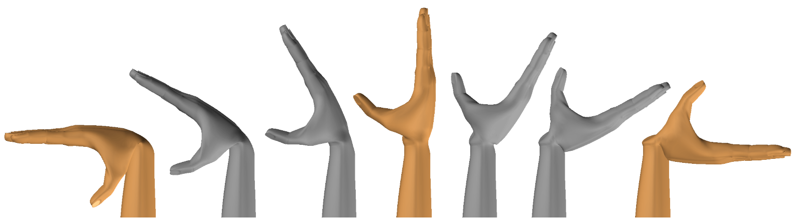

Figure 4: Range of targets using the example of wrist flexion, rest and wrist extension. The levels from left to right refer to full (1.0) wrist flexion, 0.67 wrist flexion, 0.33 wrist flexion, rest, 0.33 wrist extension, 0.67 wrist extension, full (1.0) wrist extension. For clarification: For ML training we only used the beige actions, while the participant were asked to match all of the target configurations depicted here.

In the training phase the user only performed the first (full wrist flexion), the middle (rest) and the last (full wrist extension) action. While in the goal reaching phase the user was asked not only to reach those full activations, but intermediate levels of these activations as well , i.e. at a level of 0.33 and 0.67. For each of the four ML configurations we asked the user to perform two repetitions of these five actions at three different levels (excluding relaxed/no action). Hence, we end up with 120 tasks. To assure that time dependent effects, e.g. a learning effect or fatigue, have a limited influence on our results we presented each subject with a different order of the three factors we were varying, i.e. the ML configuration, the action and the level.

The measure to evaluate the performance of each ML configuration is the success or failure in reaching each individual goal. For each task the participant had $15s$ to finish the task. Successfully finish means reaching the target area (approx. 1.2% of the work space) and staying in that area for $1.5s$. Once the target area is left the timer resets. The design of the study allows us to compare the different mixing configurations at different action levels and for different actions.

3. Experimental Results

Since successfully reaching a goal or not is a binary outcome measure, we used a log-linear analysis [10] to investigate the outcome of our study. A visualisation of the fitted model using a mosaic plot can be found in Figure 5.

The Figure is split into four major columns and three major rows, representing the four ML configurations and the three levels of activation. Furthermore, in each major column there are five minor ones, which represent the five different actions, and in each major row there are two minor ones, which represent the relative relation between successful and failed tasks for each task type§.

Two more characteristics are highlighted in this plot. First, the borders of each block are either solid or dashed. A solid line represents a positive deviation from the expected value, while a dashed line represents a negative deviation from the expected value. Second, while the majority of blocks are grey some are coloured in teal or purple. A teal block represents a positive deviation from the expected value as well , but in this case the deviation is significant. Purple blocks represent a significant negative deviation. The colour is based on the *Pearson residuals*, which is a version of a standardised residual. Values > 2 or < -2 imply that the deviation from the expected value is significant.

Remarkably, the number of cases with a significant deviation increases as the level of activation decreases: in three cases the number of failures is significantly higher than expected whereas in six cases the number of failures is significantly lower than expected. The three cases with significantly more failures all occur when the ML algorithm is trained only on sEMG data and at lower levels of activation of the degree of freedom (DOF) of wrist flexion/extension. For these three cases we have plotted the absolute error per DOF for the failed tasks in Figure 6. Additionally, for each case we performed a one-way ANOVA to compare the error of the three DOFs. The results are the following:

- $F(2, 57) = 7.027, p = 0.002$ for wrist extension at level 0.33

§ A task type is determined by the action performed, the ML configuration used and the level of activation.

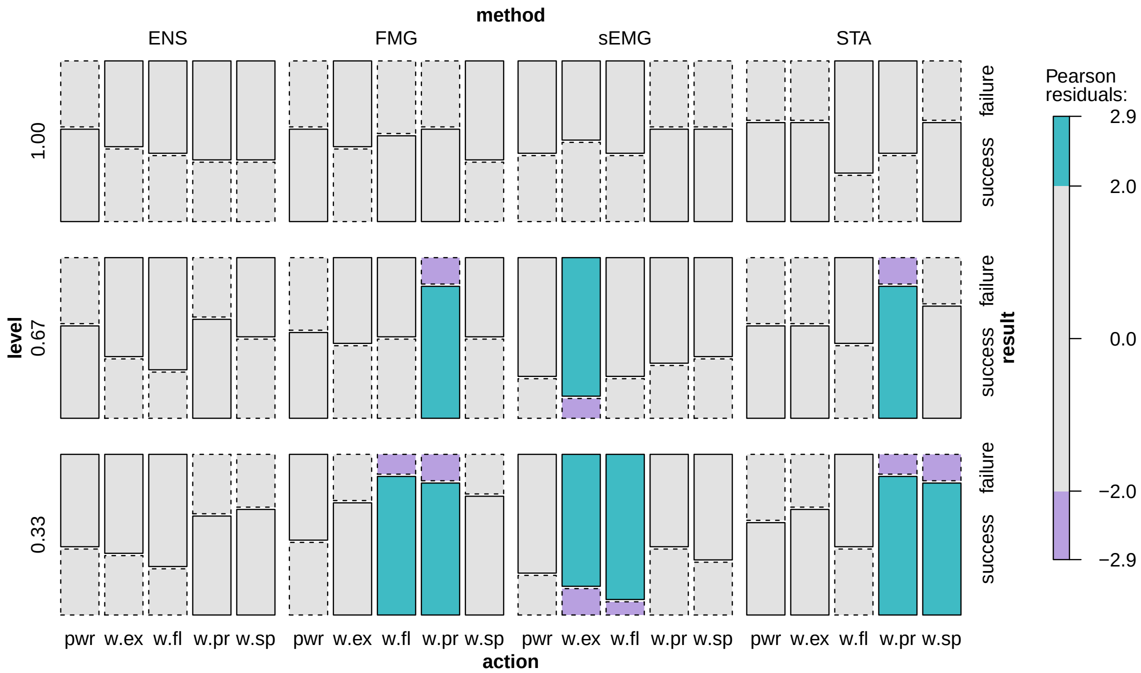

Figure 5: Mosaic plot of the full results of the experiment. Major columns represent the different ML configurations, minor columns represent the different actions (pwr: power grasp, w.ex: wrist extension, w.fl: wrist extension, w.pr: wrist pronation, w.sp: wrist supination), major rows represent different level of activation and minor rows show the relative relation between successful and failed tasks. Dashed outlines imply a negative deviation from the expected value, while solid outlines imply a positive deviation. Grey blocks mean that a deviation is not significant, while teal stands for a significant positive deviation and purple stands for significant negative deviation.

- $F(2, 63) = 4.002, p = 0.02$ for wrist flexion at level 0.33
- $F(2, 60) = 4.070, p = 0.02$ for wrist extension at level 0.67

Since significant difference was found we followed up the one-way ANOVA with a *Tukey Test*. The results can be found in Table 1.

For Figure 5 we investigate the saturated model of the log-linear regression. We chose this test, since the result of each task (success or failure) is binominal and we only preformed two repetitions of each task per subject to reduce the duration of the experiment. Therefore, we are not able to analyse the success rate in a sensible way without reducing the data along one of the factors. However, this information would provide a broader understanding of the results of the experiment. Hence, we preformed said reduction along each of the three factors, which we depict in three boxplots in Figure 7.

Furthermore, we highlight the difference between the four ML configurations with three additional plots at each activation level. For this purpose we have collapsed the two factors "action" and "configuration" into one factor and compared this new factor

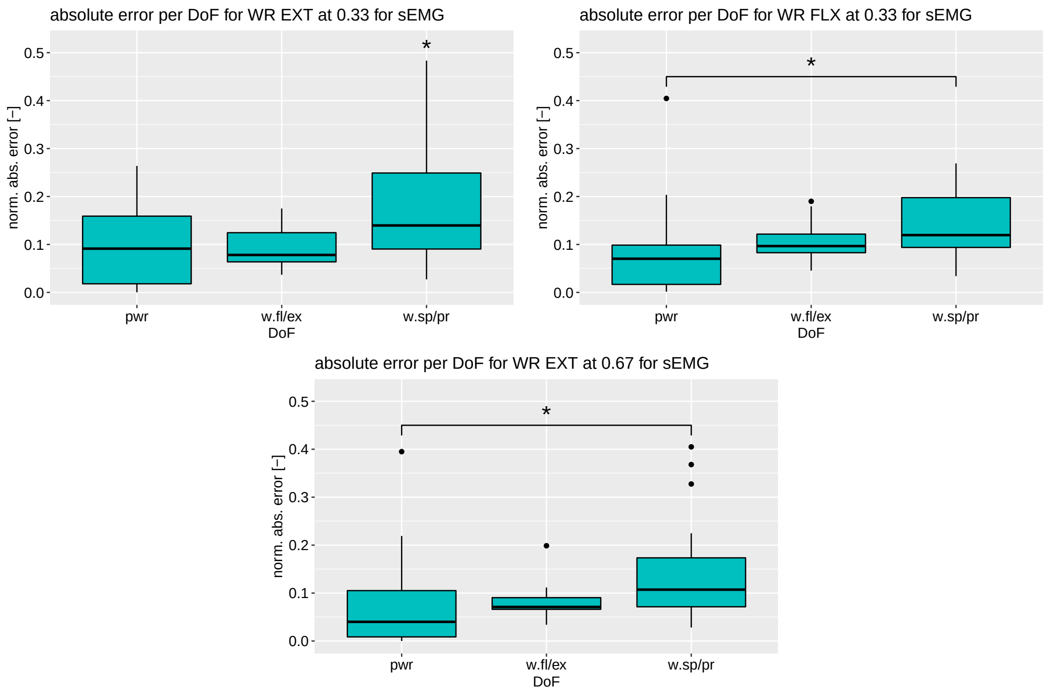

Figure 6: Boxplot of absolute error per DOF for failed tasks for the three cases, where the number of failures is significantly higher than expected. Brackets with an asterisk imply significant difference. A group with an asterisk implies significant difference from all other groups.

DOFs	p-value
w.fl/ex-pwr	0.998
w.sp/pr-pwr	0.005
w.sp/pr-w.fl/ex	0.006

(a) for wrist extension at level 0.33

DOFs	p-value
w.fl/ex-pwr	0.521
w.sp/pr-pwr	0.018
w.sp/pr-w.fl/ex	0.209

(b) for wrist flexion at level 0.33

DOFs	p-value
w.fl/ex-pwr	0.955
w.sp/pr-pwr	0.031
w.sp/pr-w.fl/ex	0.061

(c) for wrist extension at level 0.67

Table 1: Results of post-hoc *Tukey*-Test for the cases plotted in Figure 6.

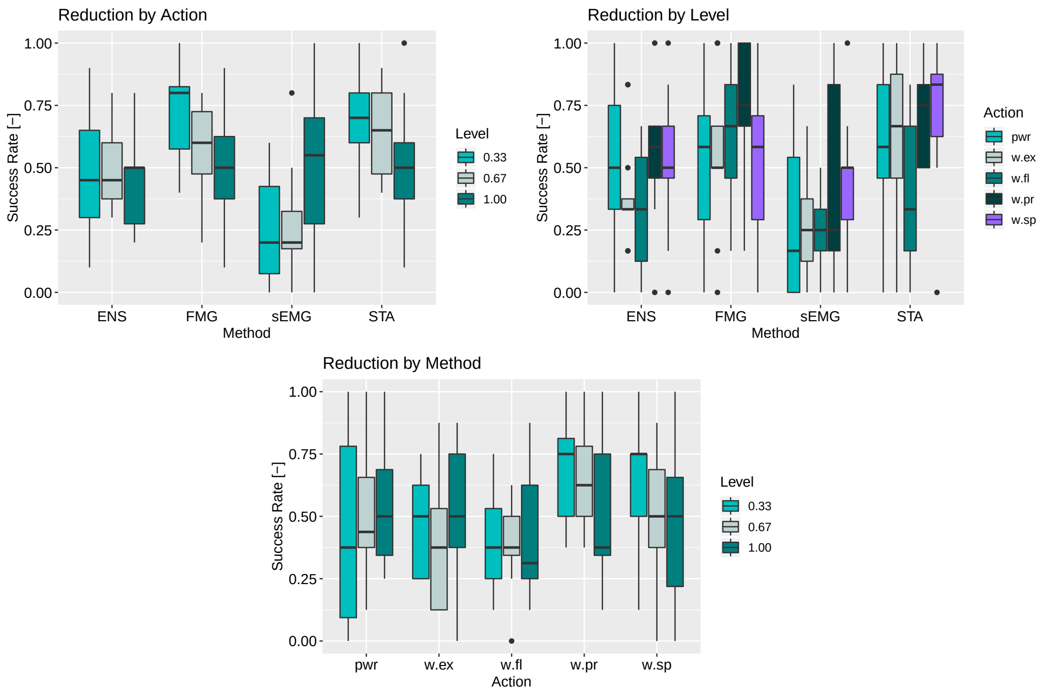

Figure 7: Boxplot of reduction by each of the three factors. The success rate is calculated or each subject and the boxplots visualise the success rate across all 12 subjects.

by the number of successful tasks (Figure 8). To some extent this is a rearrangement of Figure 5 by success rate over all subjects and repetitions.

4. Discussion and conclusions

Can FMG be proficiently coupled with sEMG for simultaneous and proportional myocontrol, and if so, how? The experimental results we obtained let us draw two major conclusions. Firstly, there are statistically significant differences in performance, according to the different sensor type set and mixing approach; secondly, the difference becomes larger at lower levels of activation.

Regarding the first issue, in general, the configurations involving FMG perform better than those involving sEMG, and by simply “stacking” FMG and sEMG sensors together we get better results than by using the more complicated ensemble mixing. When FMG alone or the stacked approach are used, we get significantly better performance for the lower activation levels of the wrist — especially for wrist pronation. The ensemble learning seems to somehow “mix” the signals in such a way to cancel out the poor performance of sEMG, but the stacked approach additionally preserves the good performances of FMG. So FMG seems, all in all, to perform better than sEMG, both alone and when combined with it.

As far as the second issue is concerned, this fact is not surprising: during low-activation tasks the magnitude of both sEMG and FMG signals is accordingly low,

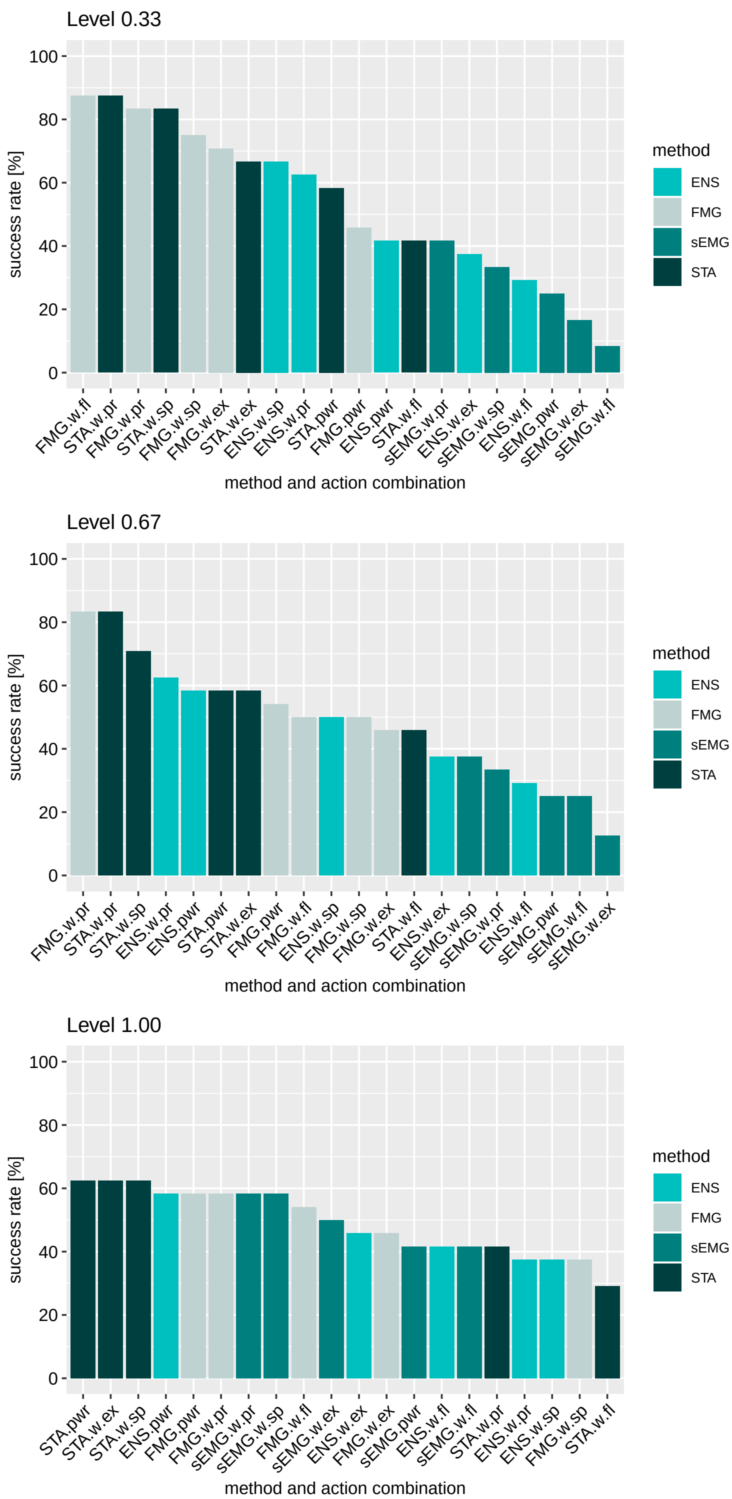

Figure 8: Number of successful tasks for each action and method combination sorted in descending order for activation level 0.33 (top), 0.67 (middle) and 1.0 (bottom). Colours highlight the ML configuration that was used.

therefore the related signal-to-noise ratio decreases, quite obviously leading to worse performances. Furthermore, at full activation level (1.00) all ML configurations perform comparably well, whereas at the lower levels differences become more evident. It is here worthwhile to stress that all ML configurations *were trained only on data provided at level 1.00, hence we claim that FMG generalises better than sEMG across activation levels.* Actually, the sEMG-alone approach performs significantly worse than expected — these cases occur for wrist flexion and extension at the lower levels of activation.

4.1. Action interference: a major reason of failure

It is interesting to have a deeper look at the reason behind these failures. We therefore compared the absolute error obtained for each DOF while performing an action — that is, not restraining the analysis to the error obtained for the DOF required for that specific action, see Figure 6. This was done to determine whether, in general, the goals could not be reached because the desired DOF could not be activated to the desired level, or because another DOF was being simultaneously unintentionally activated. All subplots of Figure 6 indicate that the source of failure was an inadvertently high wrist pronation or supination, never the inability to flex or extend the wrist. This phenomenon, which we call *action interference*, has already been observed [25] and seems to be related to the sEMG signal while it is basically absent in the FMG signal.

Figure 9 visualises this phenomenon. Using linear discriminant analysis (LDA) as a dimensionality reduction technique we created a 3D representation of the training data of one single subject. We selected the subject with the overall success rate closest to the overall median. We can clearly see that for sEMG data some actions, i.e. wrist flexion (light teal) and wrist pronation (purple), are clustered close to the rest action. Assuming an approximately linear increase in sEMG activation, one would need to "pass through" an action that is close to the rest action, when trying to reach an action that is far from the rest action. Therefore, activating an action far from the rest cluster at a low level inevitably leads to a coactivation of the action close to the rest action. This behaviour is what we call *action interference*. On the other hand, in case of FMG the action clusters seem to be evenly spread around the rest action, which would explain why *action interference* appears to be absent in this case. Here we would like to refer to the supplementary material, where the interested reader can find a rotating version of these 3D plots.

Although we cannot yet exactly say why this is the case, we speculate that it could be due to the location of the muscles involved in the actions we tested. As a matter of fact, while the muscles used to flex / extend the wrist are superficial, the muscles involved in pronation and supination are deep, inducing a relatively smaller magnitude of the sEMG signal due to the connective and fat tissue it has to travel through. As opposed to that, FMG records the superficial deformation of the forearm occurring when pronating / supinating, which has in principle nothing to do with the location of the muscles, but rather with the global bulging induced by the muscle activation.

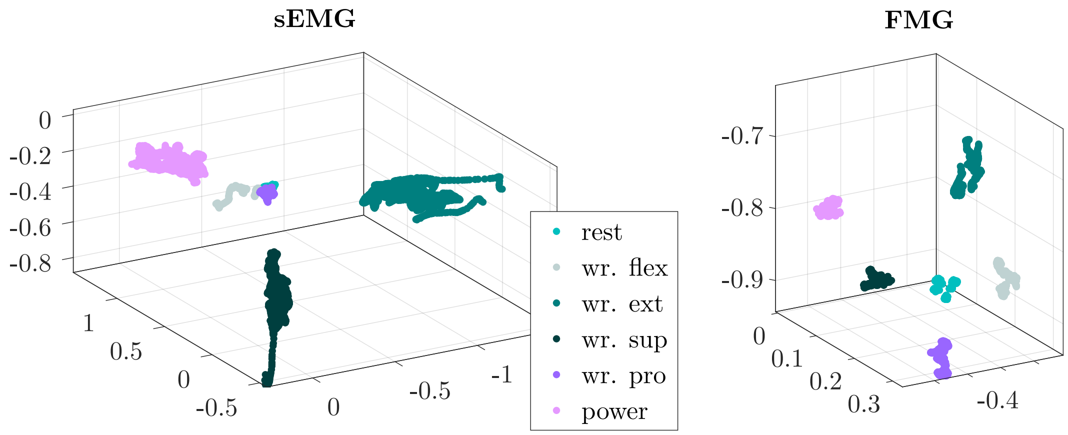

Figure 9: 3D plot of the training data of the median subject (left sEMG, right FMG). LDA was used to reduce the dimensionality to 3. (Rotating version in supplementary material)

The three graphs in Figure 8 further emphasise this behaviour. While at level 1.00 we can see an almost even distribution of different ML configurations, for the lower levels it becomes more and more clustered. We can see that for level 0.33 configurations FMG and stacked are located more to the left at high numbers of successfully accomplished tasks, while the only sEMG configuration can be found on the very right at lower number of successful tasks. The ensemble learning is situated more in the middle. The behaviour at level 0.67 appears to be in between the one at level 0.33 and level 1.00. We speculate that action interference, present whenever sEMG is part of the input space, can "deceive" both mixed approaches, therefore lowering the potentially better perforance obtained by FMG.

4.2. Conclusions and future work

FMG achieved a more robust myocontrol than sEMG in our experiment, and could better generalise to activation levels which were not present in the training set. FMG qualifies than once more as a viable and interesting replacement to sEMG in myocontrol, although more experiments are required, particularly as far as the embedding of FMG sensors in a socket is concerned [4]. The main conclusion we draw from this study is that to achieve a robust myocontrol that is capable to generalise to untrained data we need more than just sEMG sensors. Here, we have shown that the addition of FMG sensors leads to significant improvements, particularly for fine and precise manipulation. We can see, particularly in Figure 5, that to truly achieve proportionality, that means reliable control along the full spectrum of activations, we can not only rely on sEMG sensor, but need additional information.

We were able to identify the *action interference* of two DOF of the wrist to be the source of failure at low levels of activation, when using sEMG sensors. This is not the first time we encountered this issue and we already launched investigation to find a solution [25]. However, for FMG this interference does not seem to be present. The separability is preserved across the full range of activation and therefore allows fine and precise manipulation. As a general way of eliminating action interference from myocontrol, we envision that one or more quality indexes could be devised, leading to the possibility of ruling out interference even before it would actually happen [25], by increasing or changing the sensor array and/or by extracting different features from the signals.

As a further remark, our comparison shows no advantage of mixing sEMG information with FMG over only using FMG information. This is a very interesting finding. As a last remark, note that this investigation was performed in a seated position without large scale motion of the arm and/or subject and without external load on the hand/prosthesis. These conditions could influence the performance, and lifting this assumption is subject to future investigations.

Acknowledgments

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References

[1] C. Ahmadizadeh, L. K. Merhi, B. Pousett, S. Sangha, and C. Menon. Toward intuitive prosthetic control: Solving common issues using force myography, surface electromyography, and pattern recognition in a pilot case study. *IEEE Robotics Automation Magazine*, 24(4):102–111, Dec 2017.

[2] P. Beckerle, C. Castellini, and B. Lenggenhager. Robotic interfaces for cognitive psychology and embodiment research: a research roadmap. *Wiley Interdisciplinary Reviews - Cognitive Science*, page e1486, 2018.

[3] C. Castellini, P. Artemiadis, M. Wininger, A. Ajoudani, M. Alimusaj, A. Bicchi, B. Caputo, W. Craelius, S. Dosen, K. Englehart, D. Farina, A. Gijsberts, S. Godfrey, L. Hargrove, M. Ison, T. Kuiken, M. Markovic, P. Pilarski, R. Rupp, and E. Scheme. Proceedings of the first workshop on peripheral machine interfaces: going beyond traditional surface electromyography. *Frontiers in Neurorobotics*, 8(22), 2014.

[4] E. Cho, R. Chen, L.-K. Merhi, Z. Xiao, B. Pousett, and C. Menon. Force myography to control robotic upper extremity prostheses: A feasibility study. *Frontiers in Bioengineering and Biotechnology*, 4:18, 2016.

[5] M. Connan, E. Ruiz Ramírez, B. Vodermayer, and C. Castellini. Assessment of a wearable force- and electromyography device and comparison of the related signals for myocontrol. *Frontiers in Neurorobotics*, 10(17), 2016.

[6] F. Cordella, A. L. Ciancio, R. Sacchetti, A. Davalli, A. G. Cutti, E. Guglielmelli, and L. Zollo. Literature review on needs of upper limb prosthesis users. *Frontiers in Neuroscience*, 10:209, 2016.

[7] T. G. Dietterich. Ensemble learning. *The handbook of brain theory and neural networks*, 2:110–125, 2002.

[8] S. M. Engdahl, B. P. Christie, B. Kelly, A. Davis, C. A. Chestek, and D. H. Gates. Surveying the interest of individuals with upper limb loss in novel prosthetic control techniques. *Journal of NeuroEngineering and Rehabilitation*, 12(1):53, 2015.

[9] Y. Fang, N. Hettiarachchi, D. Zhou, and H. Liu. Multi-modal sensing techniques for interfacing hand prostheses: A review. *IEEE Sensors Journal*, 15(11):6065–6076, Nov 2015.

[10] A. Field, J. Miles, and Z. Field. *Discovering statistics using R*. Sage publications, 2012.

[11] F. R. Finley and R. W. Wirta. Myocoder studies of multiple myopotential response. *Archives of Physical Medicine and Rehabilitation*, 48(11):598–601, 1967.

[12] A. Fougner, Ø. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker. Control of upper limb prostheses: Terminology and proportional myoelectric control - a review. *IEEE Trans Neur Syst Rehab Eng*, 20(5):663–677, 2012.

[13] A. Gijsberts, R. Bohra, D. Sierra González, A. Werner, M. Nowak, B. Caputo, M. Roa, and C. Castellini. Stable myoelectric control of a hand prosthesis using non-linear incremental learning. *Frontiers in Neurorobotics*, 8:8, 2014.

[14] N. Jiang, I. Vujaklija, H. Rehbaum, B. Graimann, and D. Farina. Is accurate mapping of emg signals on kinematics needed for precise online myoelectric control? *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 22(3):549–558, May 2014.

[15] J. Lobo-Prat, P. N. Kooren, A. H. Stienen, J. L. Herder, B. F. Koopman, and P. H. Veltink. Non-invasive control interfaces for intention detection in active movement-assistive devices. *Journal of NeuroEngineering and Rehabilitation*, 11(1):168, 2014.

[16] R. Merletti, A. Botter, C. Cescon, M. Minetto, and T. Vieira. Advances in surface EMG: Recent progress in clinical research applications. *Critical reviews in biomedical engineering*, 38(4):347–379, 2011.

[17] R. Merletti, A. Botter, A. Troiano, E. Merlo, and M. Minetto. Technology and instrumentation for detection and conditioning of the surface electromyographic signal: State of the art. *Clinical Biomechanics*, 24:122–134, 2009.

[18] M. Nowak, B. Aretz, and C. Castellini. Wrist and grasp myocontrol: Online validation in a goal-reaching task. In *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 132–137, Aug 2016.

[19] M. Nowak and C. Castellini. The let procedure for prosthetic myocontrol: Towards multi-dof control using single-dof activations. *PLOS ONE*, 11(9):1–20, 09 2016.

[20] M. Nowak, T. Eiband, and C. Castellini. Multi-modal myocontrol: Testing combined force and electromyography. In *Proceedings of ICORR - International Conference on Rehabilitation Robotics*, 2017.

[21] M. Ortiz-Catalan, F. Rouhani, R. Brånemark, and B. Håkansson. Offline accuracy: A potentially misleading metric in myoelectric pattern recognition for prosthetic control. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 1140–1143, Aug 2015.

[22] G. Patel, M. Nowak, and C. Castellini. Exploiting knowledge composition to improve real-life hand prosthetic control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(7):967–975, July 2017.

[23] B. Peerdeman, D. Boere, H. Witteveen, R. H. in 't Veld, H. Hermens, S. Stramigioli, H. Rietman, P. Veltink, and S. Misra. Myoelectric forearm prostheses: State of the art from a user-centered perspective. *Journal of Rehabilitation Research and Development*, 48(6):719–738, 2011.

[24] S. L. Phillips and W. Craelius. Residual kinetic imaging: A versatile interface for prosthetic control. *Robotica*, 23(3):277–282, May 2005.

[25] L. Rauh. Optimizing myocontrol for daily-life activities. Technical report, Technische Universität München, September 2017.

[26] V. Ravindra and C. Castellini. A comparative analysis of three non-invasive human-machine

interfaces for the disabled. *Frontiers in Neurorobotics*, 8(24), 2014.

[27] D. Sierra González and C. Castellini. A realistic implementation of ultrasound imaging as a human-machine interface for upper-limb amputees. *Frontiers in Neurorobotics*, 7(17), 2013.

[28] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken. Target achievement control test: Evaluating real-time myoelectric pattern recognition control of multifunctional upper-limb prostheses. *Journal of Rehabilitation Research & Development (JRRD)*, 48(6):619–628, 2011.

[29] I. Strazzulla, M. Nowak, M. Controzzi, C. Cipriani, and C. Castellini. Online bimanual manipulation using surface electromyography and incremental learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(3):227–234, March 2017.

[30] I. Vujaklija, A. D. Roche, T. Hasenoehrl, A. Sturma, S. Amsuess, D. Farina, and O. C. Aszmann. Translating research on myoelectric control into clinics—are the performance assessment methods adequate? *Frontiers in Neurorobotics*, 11:7, 2017.

[31] M. Wininger, N. Kim, and W. Craelius. Pressure signature of forearm as predictor of grip force. *Journal of Rehabilitation Research and Development*, 45(6):883–892, 2008.

[32] D. Yungher, M. Wininger, W. Baar, W. Craelius, and A. Threlkeld. Surface muscle pressure as a means of active and passive behavior of muscles during gait. *Medical Engineering & Physics*, 33:464–471, 2011.

Publication 2 Simultaneous and Proportional Real-Time Myocontrol of up to Three Degrees of Freedom of the Wrist and Hand

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Simultaneous and Proportional Real-Time Myocontrol of up to three Degrees of Freedom of the Wrist and Hand

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***Abstract*— Achieving robust, intuitive, simultaneous and proportional control over multiple degrees of freedom (DOFs) is an outstanding challenge in the development of myoelectric prosthetic systems. Since the priority in myoelectric prosthesis solutions is robustness and stability, their number of functions is usually limited. *Objective:* Here, we introduce a system for intuitive concurrent hand and wrist control, based on a robust feature-extraction protocol and machine-learning. *Methods:* Using the mean absolute value of high-density EMG, we train a ridge-regressor (RR) on only the sustained portions of the single-DOF contractions and leverage the regressor's inherent ability to provide simultaneous multi-DOF estimates. In this way, we robustly capture the amplitude information of the inputs while harnessing the power of the RR to extrapolate otherwise noisy and often overfitted estimations of dynamic portions of movements. *Results:* The real-time evaluation of the system on 13 able-bodied participants and an amputee shows that almost all single-DOF tasks could be reached (96% success rate), while at the same time users were able to complete most of the two-DOF (62%) and even some of the very challenging three-DOF tasks (37%). To further investigate the translational potential of the approach, we reduced the original 192-channel setup to a 16-channel configuration and the observed performance did not deteriorate. Notably, the amputee performed similarly well to the other participants, according to all considered metrics. *Conclusion:* This is the first real-time operated myocontrol system that consistently provides intuitive simultaneous and proportional control over 3-DOFs of wrist and hand, relying on only surface EMG signals from the forearm. *Significance:* Focusing on reduced complexity, a real-time test and the inclusion of an amputee in the study demonstrate the translational potential of the control system for future applications in prosthetic control.**

***Index Terms*— bionics, hand, high-density EMG, myocontrol, prosthetics, ridge-regression, surface EMG**

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I. Introduction

UPPER limb deficiency is a consequence of traumatic incidents, underlying pathological conditions, comorbidity or a genetic predicament. The resulting functional impairment affects almost every aspect of daily living. For most acquired amputations, and some congenital limb disorders, prosthetic fittings are offered as a primary form of functional support. Most commercially available prosthetic hands provide a small number of selected functions, such as grasping and some form of wrist adjustment, which are controlled individually in a proportional fashion [1]. The most advanced systems rely on the use of surface electromyography (EMG) to establish an interface that decodes the user's motor intent [2].

Commercial myoelectric devices detect EMG signals from an antagonistic pair of remnant muscles (e.g. wrist flexors/extensors) and map them into proportional control of the available prosthetic functions (e.g. gripper open/close) [1]. The access to other available prosthetic degrees of freedom (DOFs), such as wrist rotation, is gained by introducing a switching event that can be determined by a cocontraction or a pulsed signal [3]. While highly robust, this state machine control is unnatural and not suited for restoring dexterous functions. For this reason, myoelectric prostheses have a high rate of abandonment by patients [4].

More recent control approaches consist of EMG signal classification across a finite set of classes (prosthetic functions) [5]–[7] and regression over multiple DOFs [8]. While classification methods usually provide a sequential control (one function at a time), regression-based controllers inherently support concurrent activations of multiple functions. On the other hand, robust regression control of more than two DOFs in transradial amputees has been proven challenging. In Hahne et. al. [9] such a system is investigated in ADL-like assessment tasks. They claim, increasing the number of DOFs to control beyond two becomes unfeasibly due to

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increased number of combinations to train [10]. In Ortiz-Catalan et. al. [11] a three-DOF control is reported using a different control approach than the one to be introduced in this work and the one presented by Hahne et. al. [9]. Instead of controlling the position of a prosthesis directly (position control), the velocity to reach a certain DOF configuration is commanded. This allows a wearer to perform a multi-DOF activation either by sequential or simultaneous activation of the involved DOFs. Ortiz-Catalan et. al. [11] do not indicate the amount of simultaneous activation present in reaching two- or three-DOF tasks. In Smith et. al. [12] on the other hand, a further study involving a three-DOF controller, the usage of simultaneity is explicitly investigated. The highest task-specific percentage reported is less than 50% (two-DOF tasks). All these approaches require explicit training of combined activations and only in Hahne et. al. [9] simultaneous two-DOF activation is required to achieve the respective goals.

A further challenge in current myoelectric controllers is the lack of robustness in the presence of instabilities due to altered motor control [13] and methodological factors [14], [15]. Certain academic efforts have been dedicated into tackling this issue [16]–[18] however, a clinically viable solution is yet to be found. At the same time, the induced controller instabilities lead to a lack of predictability which is paramount for establishing an engaging human-machine interface [19]–[21].

Moreover, the usage of more complex control algorithms, e.g. non-linear ones, has not led to significant improvement compared to simpler ones, e.g. linear models [22], [23]. An example of advanced algorithms was presented by Ameri et. al. [24]. The study evaluates a *regression convolutional neural network* offline and in a two-DOF goal-reaching task. Impressive advantages of this approach are a 100% success rate and no need to engineer EMG features. However, these results require training of simultaneous activations (difficult for higher number of DOFs), a velocity control (yet a very high level of simultaneous activation can be seen in the results), and additional engineering required for the design and tuning of the neural network. Furthermore, the possibility for a user to consistently anticipate the behaviour of the controller allows the simpler solutions to harness the power of human motor learning and thus effectively increase the robustness of the interface [25], [26].

Taking all these points into consideration and in order to avoid negative effects of overfitting [27], we propose a three DOFs simultaneous and proportional estimator of wrist and hand actions based on ridge-regression which is trained only on the sustained portions (steady state) of single-DOF contractions, but is tested on multiple activation levels and multi-DOF activation (up to three-DOF combinations). Since our approach resembles a position control scheme, two- and three-DOF targets can *only* be reached using simultaneous activation. Controlling multiple DOFs simultaneously and proportionally has been investigated using high-density EMG under various arrangements employing a velocity control approach, which not necessarily requires simultaneous activation [28], [29].

In this study we focus on the translational potential of our approach. Therefore, we tested the robustness of the performance not only using a high-density EMG with 192 sensors, but also with a reduced sensor arrangement with 16 sensors. Robustness here refers to control stability, e.g. due to changes in the signal during the experiment. The influence of electrode shift or other perturbations are not explicitly tested. To evaluate our approach, we conducted a set of real-time on-screen tests with a group of able-bodied participants and an amputee.

A preliminary version of this work has been reported previously [30].

II. Motion Estimation and Control Algorithm

In order to provide the users with predictable, intuitive and robust myocontrol, the established interface should ideally be consistent and transparent in the way it maps the inputs (the EMG signals) into output control commands (prosthetic motions). This may be achieved by providing as close to linear mapping as possible, and by ensuring system robustness through appropriate signal conditioning and output estimation algorithm design (training) procedure. In this section we describe our proposal for designing this system. We initially describe the EMG signal conditioning, which is followed by the details of the applied motion estimation regression algorithm and the workings of the resulting controller.

EMG signal processing: In order to provide robust inputs to the motion estimation algorithm, the raw acquired EMG signal is filtered by a $5th$ order Butterworth bandpass filter in the frequency range $20Hz{-}500Hz$. Furthermore, in order to compensate for power-line interference, a $2nd$ order Butterworth band stop filter with cut-off frequencies $45Hz$ and $55Hz$ was applied to the signal. Then, the envelope of the filtered EMG signals was used as input to the regressor. EMG amplitude envelope was selected as it is a robust, commonly used signal feature in myocontrol, which is linearly related to force [31]. The envelope was extracted from the raw EMG by estimates of the root mean square (RMS) values in $100ms$ intervals with an overlap of $90ms$. No channel-wise normalisation was performed, in order to avoid amplification of channels with low signal-to-noise ratio, which could negatively influence the regressor.

Machine Learning: In order to decode user intention, a *Ridge Regression* motion estimation algorithm was employed. The algorithm needs to be trained using representatively labelled EMG data. Contrary to previous regression studies in myocontrol [12], [22], [32], we propose to train the algorithm exclusively on data recorded during steady (constant force) contractions while omitting the dynamic segments from the training set. This approach to training is commonly used with classification methods [33]–[35], but can support users who have difficulties with phantom movements [36], [37]. Here it is chosen in order to reduce the training data variability which reinforces the linear behaviour of the controller, thus potentially increasing the robustness by ensuring the predictability of the controller. Similar ideas have been used to deal with uncertainties in classification approaches [38].

Under the assumption of linearity, the Ridge Regression estimator interpolates the intermediate activations to provide proportional control and is applied in the following form:

$$\hat{\boldsymbol{y}} = \boldsymbol{W}\boldsymbol{x} \quad \text{with} \quad \boldsymbol{W} = (\boldsymbol{X}^T\boldsymbol{X} + \lambda\boldsymbol{I})^{-1}\boldsymbol{X}^T\boldsymbol{Y} \tag{1}$$

where $\hat{\boldsymbol{y}}$ denotes the predicted hand/wrist DOFs, $\boldsymbol{W}$ are the regression weights, and $\boldsymbol{x}$ denotes a sample of EMG features. Ridge Regression is a regularised version of least-squares regression. The second part in Equation 1 represents the regularisation $\lambda\boldsymbol{I}$, with λ denoting the regularisation parameter and $\boldsymbol{I}$ the identity matrix. The parameter λ was set to 1 as previous studies have indicated this value to be well fit for a wide range of users [37], [39]. The regularisation counters poorly conditioned problems and provides solutions with a lower norm. Furthermore, $\boldsymbol{X}$ stands for the design matrix with all samples of EMG features collected during the algorithm training and $\boldsymbol{Y}$ represents the corresponding hand/wrist configurations. This machine learning (ML) method is one of the fundamental regression techniques, and due to its low computational cost and predictive behaviour it has been used for myoelectric control in previous studies [22], [40]–[42].

Resulting Controller: For the purpose of providing control over multiple DOFs, each DOF is assigned to one regressor, which is trained on both extends of the DOF, e.g. the DOF *wrist rotation* is trained with both *wrist pronation* ($y = 1$) and *wrist supination* ($y = -1$). The output of the controller are real numbers in the range of -1 to 1 and correspond to the activation of a certain DOF rather than to specific forces or joint angles. Therefore, the user is able to utilise the full spectrum of *intermediate* and/or *combined* gesture activations, even though only the *full* activations of *individual* gestures have been collected during ML training. In order to further improve user experience, depending on the personal preferences, either a fifth or a seventh-order moving-average filter was applied to the predicted output values effectively reducing the control jitter. With the windowing of $100ms$ and the delay introduced by the output filtering, the perceived delay remained well under the real-time threshold of $300ms$ [43]. Considering the treatment of the input signals, the applied motion estimation algorithm, and the conditioning of the estimated outputs, the overall control strategy proposed here provides a near-linear translation of EMG readings from the forearm to estimated activations of DOFs of the wrist and hand. A visualisation of the intermediate steps of the resulting controller can be found in the Supplementary Material.

III. Experiment Design and Evaluation

The proposed control algorithm was tested in a real-time virtual environment. The experimental setup included two arrangements with different numbers of EMG channels. The recruited study participants were asked to complete a number of goal-reaching tasks requiring proportional articulation of up to three wrist and hand DOFs concurrently. An extensive analysis of the online performance metrics has been done in order to determine the translational potential of this control approach.

A. Experimental Setup

The main setup components consisted of a high-density EMG acquisition device, a laptop used for computation and execution of the control algorithm, and an external screen used to show visual cues and the online predicted gestures to the participants (Figure 1a).

We recruited 13 able-bodied participants (age 27.5 ± 3, 5 female, 8 male) and one amputee (age 35, male) for the experiments. All participants were provided with a description of the experiment with associated risks and signed an informed consent form after all their questions were answered. The study was approved by the local ethics committee of Imperial College London (ethical approval number: 18IC4685).

Three 8-by-8 ELSCH064NM3 electrode grids were applied around the full circumference of the proximal part of the forearm of each participant. In case of the amputee only two matrices were fitted due to the small dimensions of the residual limb. The acquisition of these 192 monopolar channels (128 for the amputee was realised through a custom made Matlab (Mathworks, Natick, MA, USA) software using the *EMG-USB2+* amplifier by OTBioelettronica (Turin, Italy). Reference electrodes were placed on the wrist of the participants (black band in Figure 1a) and the data acquisition was performed at $2048Hz$.

All computations were performed on a Windows 10 laptop with a $2.2Ghz$ Intel Core i7 CPU and $16GB$ RAM.

B. Experimental Protocol

Based on user surveys [44], six gestures along three DOFs of hand and wrist were selected. These were: *relaxed state*, *power grasp*, *wrist flexion*, *wrist extension*, *wrist pronation* and *wrist supination*.

In order to train the Ridge Regression estimation algorithm, the subjects were first instructed, using the visual cues shown in Figure 1c, to perform three repetitions of the desired gestures at a strong, but comfortable levels of force. During these contractions, only $2s$ of sustained EMG data were recorded and the remaining dynamic portions were excluded. These recordings were then synthetically labelled denoting the cued gesture (no kinematics or kinetics were acquired). No activation (relaxed state) was labelled with $y = 0.0$, while the $2s$ steady-state data was labelled with either $y = 1.0$ (e.g. wrist flexion) or $y = -1.0$ (e.g. wrist extension) depending on the direction of the specific DOF. Any data corresponding to the transition between relaxed and steady state was neglected as previously described.

Upon successful system training, the users were prompted to get familiar with the control and the user interface (UI). After about ten minutes of familiarisation, the participants were instructed to reach different targets on the screen across the DOFs of interest.

These targets were presented to the user in an abstract fashion, as already done in previous studies [45], [46]. This experimental protocol meets the requirements of the later defined Target Achievement Control (TAC) test [47]. Figure 1c shows the goal-reaching UI with two vertical arrows. These arrows were shown on the screen and the user was asked to

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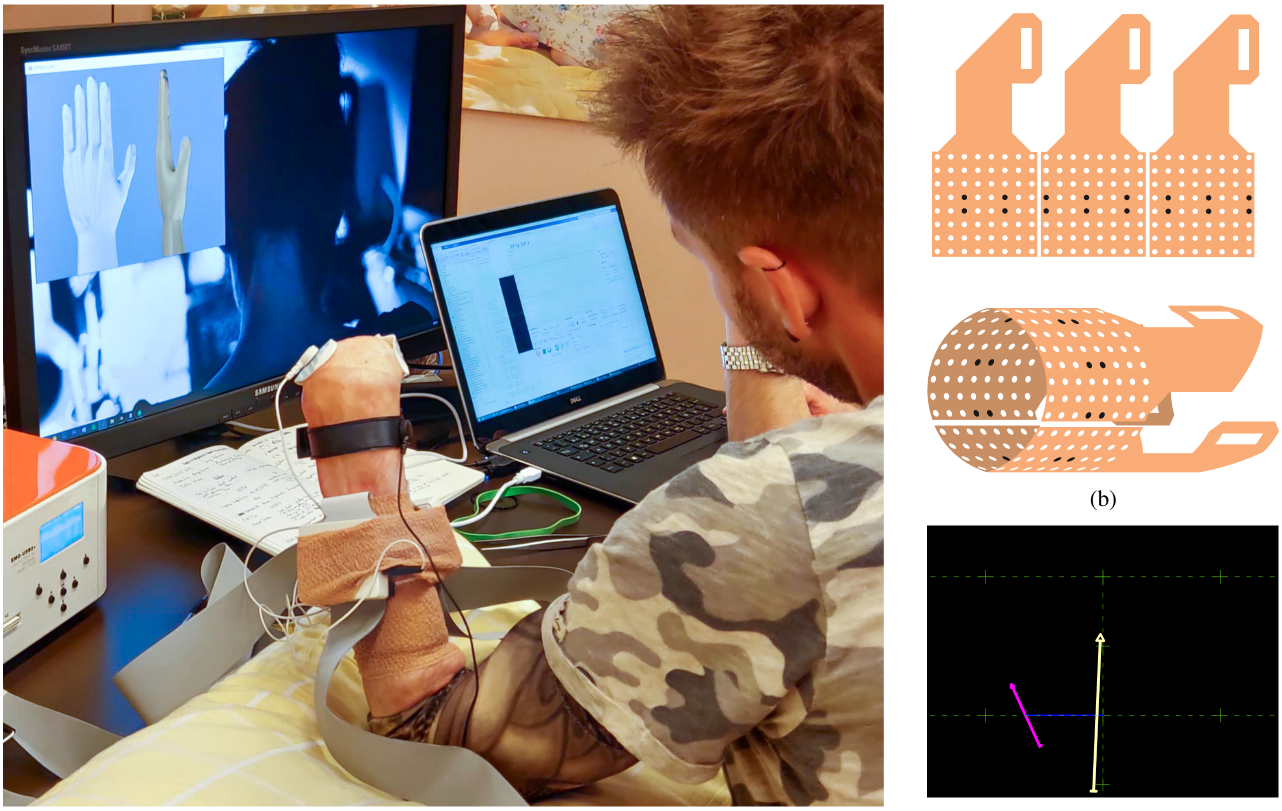

(a) (b) (c)

Fig. 1: Overview of the experimental setup: (a) hardware setup with *EMG-USB2+* amplifier, external screen showing motion prediction and target cue, and participant equipped with two (only in case of amputee, otherwise three) 8x8 sensor matrices; (b) visualisation of the arrangement of the sensor matrices and of the reduced sensor set (highlighted in black); (c) goal-reaching UI: with three-DOF combined target in pink and current prediction in yellow

align them. For each of the DOFs, the arrow would change one of its properties. Translation movement left and right was controlled using the *wrist flexion* and *wrist extension*, rotation was controlled using *wrist pronation* and *wrist supination* and performing a *power grasp* made the arrow shrink. The objective of each task was to reach the target and to remain in its proximity (the error threshold was set to 15% of the normalised work space) for at least $0.3s$. Leaving the target area led to a reset of this dwell time. The user had $20s$ to complete each task, after which the next target was displayed. Reaching the target area was visually indicated to the participant by a change of colour of the arrow from yellow to green. The colour changed back to yellow if the user left the target area. In case the task was not successfully accomplished and the timeout of $20s$ was reached, the colour of the target changed to red and the user was instructed to fully relax before resetting for the next task.

In addition to the arrow representation of the tasks and the control, participants were also shown two hand models. These two hand models, a grey one for the target posture and a beige one for the current prediction, are shown in Figure 1a. However, the users mostly preferred the arrow-based UI.

A total of 24 targets comprised of either individual gestures, such as *power grasp*, or combinations, such as concurrent activation of *power grasp* and *wrist pronation*, were shown to the participants. An added difficulty to the testing was included by introducing intermediate levels of these actions. This was done for both individual gestures, e.g. 30% *wrist pronation*, as well as for combinations, e.g. 30% *wrist pronation* combined with 80% *power grasp*. The targets with the highest difficulty were those which involved a combination of gestures along all three DOFs. Given that the system evaluation focused on the viability of the solution, the overall selection of tasks was based on the ability to conduct robust systematic testing while ensuring not to overburden and fatigue the participants. This meant selecting task activation levels in relation to the increasing difficulty of the concurrent DOF manipulation [47] and thus focusing on the combination levels which are more commonly used during ADLs [48]. A list of gestures used for both training the algorithm and real-time testing is reported in Table I and a visualisation of the execution of ten randomly selected tasks can be found in the Supplementary Material. Furthermore, the Supplementary Material also contains a short clip of the amputee performing a task.

To further test the limits of the approach, four out of the 13 able-bodied participants were selected at random and were asked to perform an additional experiment with a reduced number of sensors and the same 24 goals from Table I. A

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TABLE I: Training actions and goals with further categorical information.

		Wr. Fl./Ex.	Wr. Sp./Pr.	Grasp	TargetDoFs	wFlex/Ext	wRot	wGrasp	AccLvl
training data		1.00	0.00	0.00	-	-	-	-	-
		-1.00	0.00	0.00	-	-	-	-	-
		0.00	1.00	0.00	-	-	-	-	-
		0.00	-1.00	0.00	-	-	-	-	-
		0.00	0.00	1.00	-	-	-	-	-
		0.00	0.00	0.00	-	-	-	-	-
testing data	1	0.30	0.00	0.00	1	yes	no	no	0.30
	2	-0.30	0.00	0.00	1	yes	no	no	0.30
	3	0.00	0.30	0.00	1	no	yes	no	0.30
	4	0.00	-0.30	0.00	1	no	yes	no	0.30
	5	0.00	0.00	0.30	1	no	no	yes	0.30
	6	0.00	0.00	0.55	1	no	no	yes	0.55
	7	0.80	0.00	0.00	1	yes	no	no	0.80
	8	-0.80	0.00	0.00	1	yes	no	no	0.80
	9	0.00	0.80	0.00	1	no	yes	no	0.80
	10	0.00	-0.80	0.00	1	no	yes	no	0.80
	11	0.00	0.00	0.80	1	no	no	yes	0.80
	12	0.00	0.00	1.00	1	no	no	yes	1.00
	13	0.55	0.55	0.00	2	yes	yes	no	1.10
	14	0.55	-0.55	0.00	2	yes	yes	no	1.10
	15	-0.55	0.55	0.00	2	yes	yes	no	1.10
	16	-0.55	-0.55	0.00	2	yes	yes	no	1.10
	17	0.55	0.00	0.80	2	yes	no	yes	1.35
	18	-0.55	0.00	0.80	2	yes	no	yes	1.35
	19	0.00	0.55	0.80	2	no	yes	yes	1.35
	20	0.00	-0.55	0.80	2	no	yes	yes	1.35
	21	0.55	0.55	0.80	3	yes	yes	yes	1.90
	22	0.55	-0.55	0.80	3	yes	yes	yes	1.90
	23	-0.55	0.55	0.80	3	yes	yes	yes	1.90
	24	-0.55	-0.55	0.80	3	yes	yes	yes	1.90

reduced set of 16 electrodes was uniformly distributed around the circumference of the forearm in pairs of two channels along the muscle fibres (black dots in Figure 1b).

C. Performance Measures

The primary performance measure was *Success*, which determines whether the participant is able to successfully complete the task of reaching a goal. Successful tasks were further analysed with three secondary performance measures: *TimeToReach*, *Speed* and *PathEfficiency*. *TimeToReach* indicates the time it takes a user to successfully accomplish a task, *Speed* is the ratio between the length of the path travelled and *TimeToReach*, and *PathEfficiency* is the ratio of the length of the shortest path from start (origin of the UI shown in Figure 1c) to endpoint (target location) and the length of the path actually taken by the user.

D. Statistical Evaluation

The primary and each of the three secondary measures were analysed individually. The tasks were chosen to cover several relevant aspects of simultaneous and proportional control. These properties were the independent factors in the statistical evaluation and their values can be found in Table I in columns 6-10 (*TargetDOFs* to *AccLvl*). *TargetDOFs* is a factor with three levels which denote the number of DOFs involved in a task (1 stands for individual gesture goals, while 2 and 3 stand for combinations of 2 or 3 gestures in a goal). *wFlex/Ext*, *wRot* and *wGrasp* indicate whether the corresponding DOF is present in a given task or not. *AccLvl* is the summation of the levels of activation for each gesture involved in a goal. This parameter tells the extent to which each gesture involved in the task should be activated. A further factor (not listed in Table I) is *SensorNumber*, which indicates whether the experiment was conducted with a full set of 192 sensors or the reduced set of 16 sensors.

The statistical analysis was performed for able-bodied participants and only statistical model comparison was done for the amputee data.

The first step was an investigation of the two major factors for evaluating the translational potential of the system, *TargetDOFs* and *SensorNumber*. These can tell how well more complex targets can be reached and how well they can be reached after the number of sensors has been reduced from 192 to 16.

For statistical model fitting of the able-bodied participants' data, all the factors were considered at first, including the interaction terms. In a stepwise process the models have been reduced by removing the factor (and all associated interaction terms) that contributed the least to the explained variance for as long as the reduction was not significantly affecting the corresponding fits. The last non-significant reduction step became the final statistical model, which was followed by post-hoc tests. The post-hoc was a pair-wise *t-test* with *Bonferroni-Correction*.

Finally, these models were extended by the data from the amputee in order to understand whether there was a significant difference.

Due to the nature of the data statistical *Multilevel Modelling* [49]–[53] has been considered. Namely, we have chosen *Linear Mixed-Effects Models* for normally distributed measures and *Generalized Linear Mixed-Effects Models* for *Success*,

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which follows a binomial distribution. These methods can deal with unbalanced samples in different groups.

IV. Results

The overview of observed performance across all measures grouped by *TargetDOFs* and *SensorNumber* is shown in Figure 2. The overall success rate with respect to the number of DOFs included in the task is displayed as a bar plot. At the same time, individual measures for *TimeToReach*, *Speed*, and *PathEfficiency* are shown as dots on top of violin plots indicating the distribution of the data. The horizontal line on each violin plot denotes its respective mean and its value is printed in black. Furthermore, all these values (with their standard errors) and the corresponding performance for the amputee participant can be found in Table II.

The performance of the four randomly selected subjects invited to complete the additional experiment with reduced number of sensors has been reported separately. For easier comparison their results for the full sensor configuration and the reduced one are shown side by side ("4 subjects" in Figure 2a). Although the four participants were selected at random, the subset resulted in a group that had a higher success rate than the pool of all participants.

A. Real-time performance analysis

In order to understand different aspects of the observed real-time performance of the system, previously described statistical models were gradually reduced with respect to all outlined factors. The reduction was done until only the factors that had a significant influence on the data remained. The final models were largely similar, yet still feature certain differences for each performance measure:

$$\begin{aligned} \textit{Success} &\sim \textit{TargetDOFs} \\ \log(\textit{TimeToReach}) &\sim \textit{AccLvl} + \textit{wGrasp} \\ \log(\textit{Speed}) &\sim \textit{AccLvl} \\ \textit{PathEfficiency} &\sim \textit{TargetDOFs} + \textit{wGrasp} \end{aligned}$$

From the initial list of six factor introduced in Subsection III-D at most two remain per model. For the performance measure *Success*, only the factor *TargetDOFs* had a significant influence on the *Success* value. Similarly, only *AccLvl* and *wGrasp* significantly influenced *TimeToReach*, only *AccLvl* significantly influenced *Speed* and only *TargetDOFs* and *wGrasp* significantly influenced *PathEfficiency*. As a remark, the factors *TargetDOFs* and *AccLvl* describe similar properties in the models regarding the difficulty of a task. Thus, they could be correlated. Calculating the *Spearman* and *Kendall* correlation confirms this notion with values of $\rho = 0.93$ and $\tau = 0.87$, respectively. Due to the stepwise factor-reduction process the influence of this property should be minimal as the addition to the explained variance is low and therefore one factor is discarded early.

Figure 3 shows the bar plot indicating the subjects' *Success* over different target types, and the violin plots for the performance with respect to the remaining three metrics. However, this time the factors were determined by the statistical model reduction instead of the default ones. Furthermore, brackets in these plots indicate the identified significant pair-wise interactions. The significant interactions are highlighted with asterisks, where '*' stands for $p \in]0.05, 0.01]$, '**' for $p \in]0.01, 0.001]$ and '***' for $p < 0.001$.

When considering the rate of success in reaching different targets, with respect to number of channels used to drive the system, the process of reducing the statistical model showed that there are no statistical differences (Figure 3a, $\chi^2(3) = 5.5346$, $p = 0.1366$ in the stepwise reduction). Similarly, the number of used sensors also had no statistically significant influence on the three secondary performance measures (*TimeToReach*: $\chi^2(10) = 7.1755$, $p = 0.7088$, *Speed*: $\chi^2(7) = 3.5986$, $p = 0.8247$, and *PathEfficiency*: $\chi^2(10) = 14.52$, $p = 0.1506$).

The only factor that did indeed impact the *Success* was the *TargetDOFs*. Targets that only involve one DOF could be reached with a success rate of 96%. However, the performance significantly decreased when the number of DOFs increased from 1 to 2 ($p < 0.001$), from 1 to 3 ($p < 0.001$) and from 2 to 3 ($p = 0.0017$).

The conducted statistical analysis has shown that subjects took significantly longer (Figure 3c, $p < 0.001$) and had a statistically less efficient reaching paths (Figure 3f, $p < 0.001$), when faced with tasks that included power grasp (*wGrasp*). No significant differences were observed in tasks that featured other DOFs (*wFlex/Ext* and *wRot*).

Analysing the data shown in Figure 3b, participants required a significantly shorter time ($p < 0.001$) to complete single DOF tasks that considered the lowest *AccLvl* (0.3) in comparison to those tasks prompting subjects to exert moderate levels of activation (0.8). This was a general trend as the complexity of tasks increased (both in terms of *AccLvl* and *TargetDOFs*).

Similarly, Figure 3d indicates that participants tended to reach higher velocities when they were prompted to complete tasks with higher *AccLvl* and *TargetDOFs*. At the same time, they took significantly less efficient paths ($p < 0.001$) when faced with tasks that involved more than a single DOF. Furthermore

B. Amputee performance

Figure 4 shows the violin plots based on the reduced statistical models for the able-bodied participants overlaid with the individual measurements of the amputee. The horizontal black line representing the mean of the able-bodied participants has now been supplemented with an additional dashed line, indicating the respective mean of the amputee. All these values (with standard errors) and the respective values for the remaining participants are reported in Table II.

This comparison indicated that the amputee subject was as successful as the other subjects ($\chi^2(3) = 2.8011$, $p = 0.4233$). In fact, the overall behaviour was similar with a reduction of the success rate as *TargetDOFs* increased (Figure 4a).

At the same time, he was completing the given tasks at comparable speeds ($\chi^2(7) = 4.379$, $p = 0.7352$). On the other hand, he required significantly more time ($\chi^2(9) = 32.286$, $p < 0.001$) and it took him almost consistently

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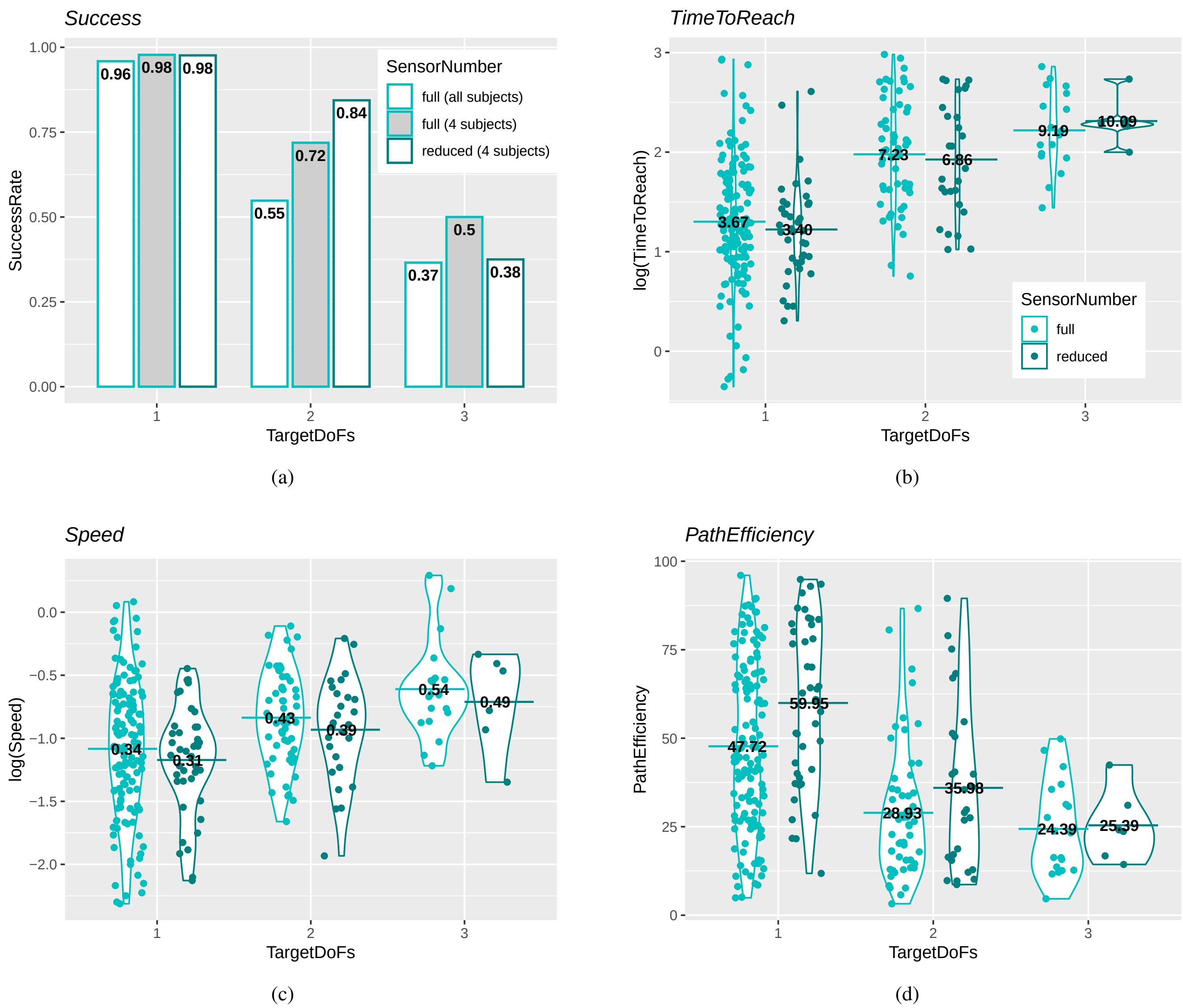

Fig. 2: Overview of the observed performance across four metrics separated by *TargetDOFs* and by *SensorNumber*

longer to complete targets with higher *AccLvl* as seen in Figure 4b. Surprisingly, the amputee subject required less time to complete tasks that included the power grasp (Figure 4c).

Finally, the amputee took significantly longer paths ($\chi^2(4) = 12.031$, $p = 0.01712$) than other participants, as shown in Figures 4e and 4f.

V. Discussion

In this study we demonstrated real-time simultaneous and proportional myocontrol over three DOFs of hand and wrist using EMG signals from the forearm muscles. The proposed paradigm enables intuitive control by relying on almost linear mapping between input commands and the target output gestures. This is achieved using a simple Ridge Regression motion estimation algorithm trained only on three repetitions of single-DOF steady-state contractions corresponding to the desired motions. The translational potential of this approach has been investigated in real-time experiments with both able-bodied subjects and an amputee, and by eventually reducing the number of EMG channels to a subset of sensors corresponding in number to those present in commercially available prostheses.

Throughout the evaluation of the proposed control algorithm, from the plots shown in Figure 3 and the statistical model analysis presented in Section IV-A, we can conclude that the number of factors that truly influence the control performance is relatively small. Looking into specifics of the observed metrics, there are three main findings to highlight.

First, the proposed approach is capable of extending single DOF control to two and even three DOF control at no additional effort (system training is done only on single-DOF data). The extension to multiple DOF is associated to a decrease in performance in complex tasks, however, the additional capability does not compromise the single-DOF control, which remained at a high success rate. Around

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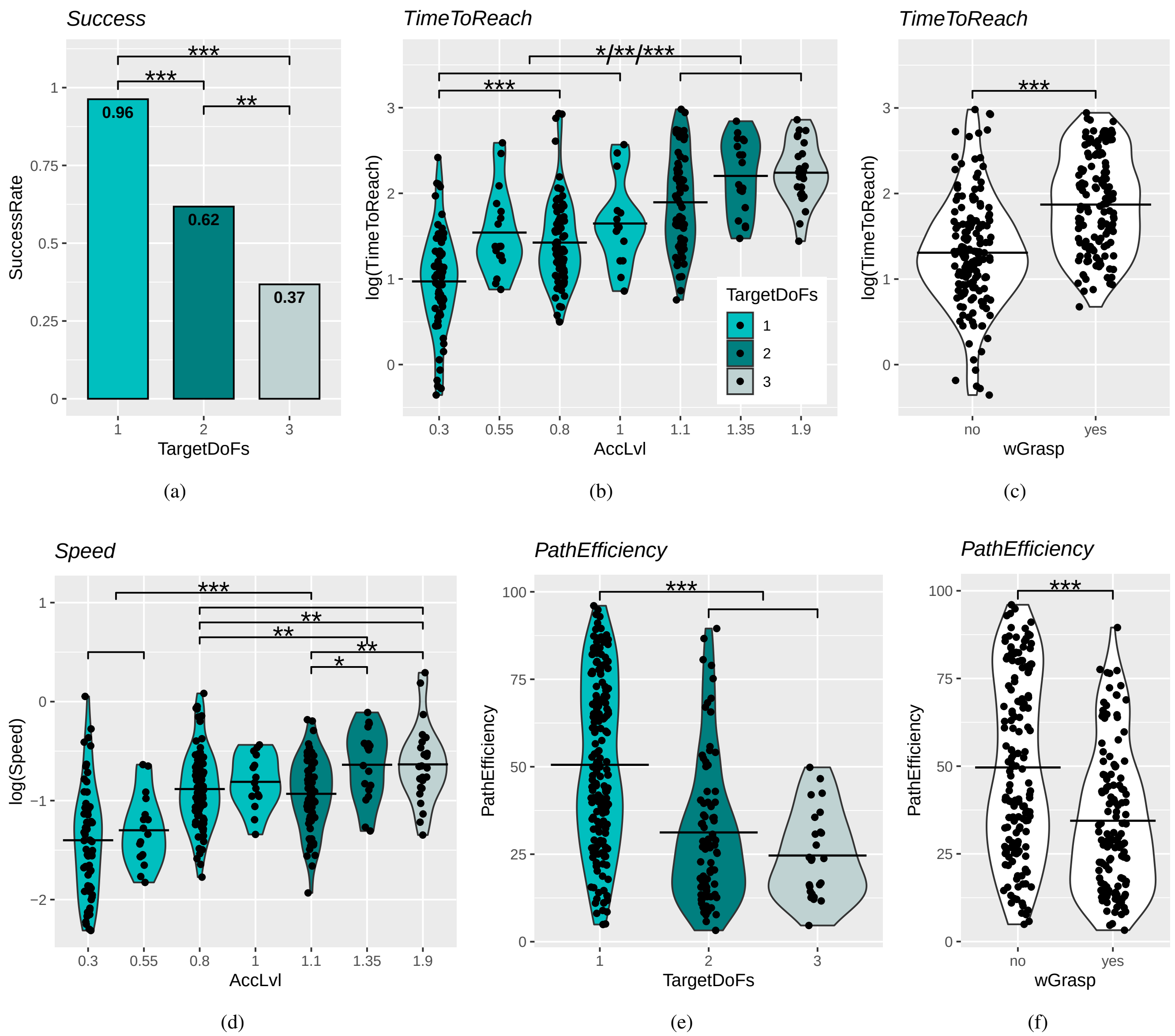

Fig. 3: Final models for all performance measures. Brackets with an asterisk represent significant difference between levels, while brackets without an asterisk represent grouping of different levels. The expression '*/**/***' indicates significant difference between groups with at least $p < 0.05$ for the individual interaction. Significance codes: $p = [0\,\text{'***'}\,0.001\,\text{'**'}\,0.01\,\text{'*'}\,0.05]$

$^2/_3$ of the tasks involving two DOFs and $^1/_3$ of the tasks involving three DOFs could be successfully completed, even though these combinations had not been specifically trained. Furthermore, proportional control over up to three DOFs was achieved without explicitly training on the dynamic portion of the training data. Potential challenges that arise from these training data segments have been linearly interpolated by the controller. Another approach is treating these segments as classes of their own [17], [18]. Similar trends and performance values have been observed previously [54], however, only two DOFs of the wrist have been considered. Barsotti et. al. [40] performed a study only training on individual DOFs and predicting combined activation for up to five finger activations. Both the SR for individual and simultaneous targets are comparable, but lower than in our study, with ca. 85% and ca. 25% respectively for linear feature. Focus of the study has been the comparison between a linear and a non-linear feature. Dealing with combinations of finger activations requires addressing a high level of physiological coupling [39]. Non-linear features can be beneficial in this scenario [40]. These and other more powerful features are potential avenues for improving our control. Furthermore, while a number of studies have used regression for natural combination of DOFs (for an overview see [55]), a simultaneous combination of three DOFs over wrist and hand with proportional capabilities using intuitive mapping has not been experimentally evaluated so far. Smith et. al. [12] and Ortiz-Catalan et. al. [11] have both performed studies regarding simultaneous and proportional control. Both studies have reached success rate similar to ours of more than 90%. These rates have also been achieved

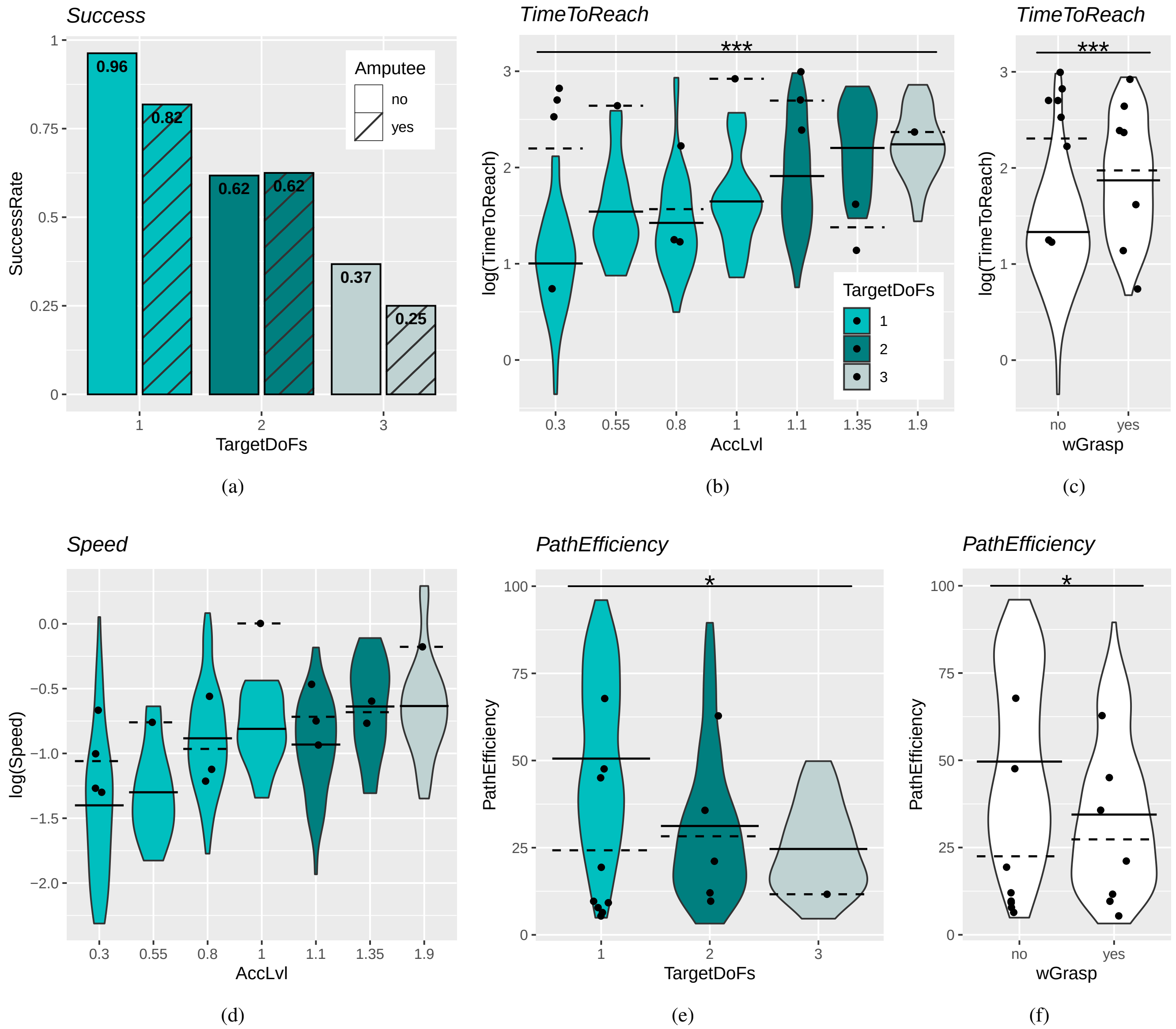

Fig. 4: Final models for the secondary performance measures updated with the performance of the amputee. Full horizontal line represents able-bodied participant sample mean and dashed horizontal line mean of amputee. The violin plots indicating the distribution of the different measure are based on the data of the non-amputee participants. Lines with an asterisk indicate that for this performance measure the difference between the amputee and the remaining participants was significant. Significance codes: $p = [0$ '***' 0.001 '**' 0.01 '*' $0.05]$

in combined tasks, while the performance in our study was significantly lower. However, in said studies the combined activations have been trained explicitly and velocity control was employed. The latter allows the participant to reach multi-DOF targets without using simultaneous activations of these DOFs. Our controller does not require explicit training and yet allows the participants to perform multi-DOF activations. Therefore, in 100% of our multi-DOF tasks simultaneity was used, while simultaneity was used in less than 50% of cases in [12]. Ortiz-Catalan et. al. [11] did not report the usage of simultaneity during target reaching.

Furthermore, it is worth noting that the control over the power grasp (*wGrasp*) seemed to have been more challenging than other gestures for able-bodied subjects and yet easier for the amputee. This was presumably due to a larger variance present in the data related to this movement as it involves more prominent co-activation of different muscle groups. As a further remark, the *power grasp* was the only DOF that had four different levels instead of three for the remaining DOFs. Additional emphasis was put on said DOF due to its importance in prosthetic control. This could have resulted in an unintentional additional difficulty in activating this DOF. On the other hand, the amputee performed better in tasks involving the *power grasp*. An explanation could be that he is a long-term (more than 5 years of daily use) user of a myoelectric prosthesis with hand open and close functionality. Therefore,

TABLE II: Mean values (± standard error of the mean, where possible) of the variables indicated in the first column for each combination of *TargetDOFs* and *SensorNumber* for the amputee participant and the remaining participants

Variable	Target DOFs	SensorNumber full	SensorNumber reduced	amputee
SR	1	0.96 ± 0.016	0.98 ± 0.024	0.82 ± 0.12
SR	2	0.55 ± 0.049	0.84 ± 0.065	0.62 ± 0.18
SR	3	0.37 ± 0.067	0.38 ± 0.16	0.25 ± 0.25
log(TTR)	1	1.30 ± 0.052	1.22 ± 0.075	2.12 ± 0.27
log(TTR)	2	1.98 ± 0.072	1.93 ± 0.11	2.17 ± 0.34
log(TTR)	3	2.22 ± 0.089	2.31 ± 0.097	2.37
TTR	1	3.67	3.40	8.31
TTR	2	7.23	6.86	8.75
TTR	3	9.19	10.09	10.68
log(SP)	1	-1.08 ± 0.046	-1.17 ± 0.066	-0.88 ± 0.14
log(SP)	2	-0.84 ± 0.049	-0.93 ± 0.079	-0.70 ± 0.080
log(SP)	3	-0.61 ± 0.091	-0.71 ± 0.16	-0.18
SP	1	0.34	0.31	0.42
SP	2	0.43	0.39	0.50
SP	3	0.54	0.49	0.84
PE	1	47.72 ± 2.02	59.95 ± 3.64	24.25 ± 7.71
PE	2	28.93 ± 2.47	35.98 ± 4.58	28.27 ± 9.77
PE	3	24.39 ± 3.03	25.39 ± 4.18	11.64

while acknowledging that this is a consideration based only on a single subject, the increase in performance on this particular DOF could be attributed to previous training and the frequent, isolated use of the specific muscles related to this particular function.

Second, the performance of the proposed system remained consistent even with a reduced number of input channels. To demonstrate the translational potential of the approach, we decreased the number of EMG channels from 192 to 16 (Figure 1b), which is a number comparable to that of sensors already available in advanced commercial solutions [5], [6]. Although we use the 16 individual sensors in a monopolar configuration, the technical complexity of such a configuration is not significantly different from an 8-channel differential arrangement, as it can be found in said commercial solutions. This reduction in number of electrodes had no significant impact on any of the observed measures. This outcome is consistent with previous work on both regression- and classification-based estimators for myocontrol [46], [56], [57]. Muceli et al. [46] have shown that a channel reduction from 192 to 6 does not negatively influence regression-based user performance, Amma et al. [56] demonstrated that going from 168 to ca. 20 sensors yields a decrease in performance from ca. 95% to ca. 80% and Rojas-Martínez et al. [57] have come to a similar result when reducing from $342-354$ channels to 27. However, our study is the first that successfully demonstrates such resilience during concurrent control of three DOFs of wrist and hand. This is an important observation, since in the process of embedding a myocontroller in a prosthetic device, a lower number of sensors can be beneficial as it drastically reduces the overall technical complexity of the device. An offline analysis further supports the online findings of no significant influence of the sensor reduction. Based on the four subject that participated in the second part of the experiment, we have used the training data of the online experiment to train four regressors with different sensor configurations, i.e. all 192 sensors, the *optimal* 16 sensors, the *optimal* eight sensor pairs, and our uniform configuration of eight sensor pairs. In a repetition-wise three-fold cross-validation we evaluated two measures of fit, i.e. *R2* and *normalised root mean square error (nRMSE)* using a forward search based on *Ridge Regression* adding iteratively the channels that results in the best fit. The results can be found in Table III.

TABLE III: Offline comparison of four sensor configurations, i.e. all 192 sensors, the *optimal* 16 sensors, the *optimal* eight sensor pairs, and uniform configuration of eight sensor pairs, for the four participants of the second part of the experiment assessed using *R2* and *normalised root mean square error (nRMSE)*.

sensor conf.	*R2*	*nRMSE*
192	0.787 ± 0.085	0.195 ± 0.037
opt. 16	0.824 ± 0.084	0.166 ± 0.027
opt. 8 pairs	0.765 ± 0.099	0.191 ± 0.027
uniform 8 pairs	0.597 ± 0.100	0.244 ± 0.018

The uniform sensor configuration has a lower fit of the data then the full sensor configuration or the optimal selection. However, in the online scenario this difference proves not to be significant. Furthermore, the optimal channel selection yields a better fit of the data then the full 192 channels, which could indicate overfit in the full-channel configuration. Since the user-specific optimal channel selection yields a better fit than the uniform selection, a potential improvement could be achieved with individual sensor placement per user.

Third, while using the proposed control approach an amputee was similarly successful in completing the presented tasks as other subjects. However, he took longer to complete them and his *PathEfficiency* was lower than the one from the remaining participants. While these results have to be considered cautiously since based on a single patient, they indicate that the proposed system has the potential to be used by amputees.

Beyond these main findings, from Figures 3d and 3e it could be argued that for higher *AccLvl* the oscillation and the instability of the provided control increases. This could be explained by the fact that with increasing *AccLvl*, and therefore also with a rise in number of DOFs that need to be addressed (*TargetDOFs*), the user has to navigate the controller in an area where the algorithm was not explicitly trained. This potentially leads to a more jittery behaviour, which is emphasized by the fact that there is no significant difference for *PathEfficiency* between two- and three-DOF tasks. System training data only consisted of single-DOF motions, thus when reaching for the targets that require combined movements, the control may become more unstable. Besides the influence of the training data a reduced *PathEfficiency* can also be explained by physiological aspects. A theoretical combination of e.g. *wrist flexion* and *power grasp* at their maximum voluntary contraction (MVC) is physiologically not possible [58]. These properties have been taken into account for the design of the goal-reaching tasks. However, specific combinations can pose added difficulty and could require less efficient reaching paths. Physiological aspects could explain the different performance for tasks involving the *power grasp*. Potentially, this unstable behaviour could be alleviated by the user gaining more experience with the controller [26] or an incremental learning scheme [41] to update training data when needed. Nevertheless, the benefit of having a very simple and quick system training, and the fact that single-DOF control remains high with combined actions still well handled, arguably outweighs the observed reduction in performance.

VI. Conclusion

We have proposed and demonstrated a system for simultaneous and proportional real-time EMG control over 3-DOFs with an intuitive interface, and minimal user and machine training. This was done by training a Ridge Regression algorithm solely on steady portions of three repetitions of the single DOF dynamic contractions of wrist and hand. Such design choice has allowed us to reduce the influence of data variability introduced by dynamic inputs and to leverage on the simplicity of the estimator.

References

[1] I. Vujaklija, D. Farina, and O. Aszmann, "New developments in prosthetic arm systems," *Orthopedic Research and Reviews*, vol. Volume 8, pp. 31–39, Jul. 2016.
[2] N. Jiang, S. Dosen, K.-R. Muller, and D. Farina, "Myoelectric Control of Artificial Limbs—Is There a Need to Change Focus? [In the Spotlight]," *IEEE Signal Processing Magazine*, vol. 29, no. 5, pp. 152–150, Sep. 2012.
[3] R. N. Scott and P. A. Parker, "Myoelectric Prostheses: State of the art," *Journal of Medical Engineering & Technology*, vol. 12, no. 4, pp. 143–151, Jan. 1988.
[4] E. Biddiss and T. Chau, "Upper-Limb Prosthetics: Critical Factors in Device Abandonment," *American Journal of Physical Medicine & Rehabilitation*, vol. 86, no. 12, pp. 977–987, Dec. 2007.
[5] Coapt LLC, "COMPLETE CONTROL Handbook," 2018.
[6] Ottobock, "Technology for people 4.0: Ottobock at OTWorld 2018," https://www.ottobock.com/en/newsroom/news/technology-for-people-4-0-ottobock-at-otworld-2018.html, May 2018.
[7] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *The Journal of Rehabilitation Research and Development*, vol. 48, no. 6, p. 643, 2011.
[8] I. Vujaklija, "Novel Control Strategies for Upper Limb Prosthetics," in *Converging Clinical and Engineering Research on Neurorehabilitation III*, ser. Biosystems & Biorobotics, L. Masia, S. Micera, M. Akay, and J. L. Pons, Eds. Cham: Springer International Publishing, 2019, pp. 171–174.
[9] J. M. Hahne, M. A. Schweisfurth, M. Koppe, and D. Farina, "Simultaneous control of multiple functions of bionic hand prostheses: Performance and robustness in end users," *Science Robotics*, vol. 3, no. 19, Jun. 2018.
[10] J. M. Hahne, S. Dahne, H.-J. Hwang, K.-R. Muller, and L. C. Parra, "Concurrent Adaptation of Human and Machine Improves Simultaneous and Proportional Myoelectric Control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 4, pp. 618–627, Jul. 2015.
[11] M. Ortiz-Catalan, B. Håkansson, and R. Brånemark, "Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 4, pp. 756–764, Jul. 2014.
[12] L. H. Smith, T. A. Kuiken, and L. J. Hargrove, "Evaluation of Linear Regression Simultaneous Myoelectric Control Using Intramuscular EMG," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 4, pp. 737–746, Apr. 2016.
[13] V. Glaser and A. Holobar, "Motor Unit Identification From High-Density Surface Electromyograms in Repeated Dynamic Muscle Contractions," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 1, pp. 66–75, Jan. 2019.
[14] C. J. De Luca, S.-S. Chang, S. H. Roy, J. C. Kline, and S. H. Nawab, "Decomposition of surface EMG signals from cyclic dynamic contractions," *Journal of Neurophysiology*, vol. 113, no. 6, pp. 1941–1951, Dec. 2014.
[15] L. Hargrove, Y. Losier, B. Lock, K. Englehart, and B. Hudgins, "A Real-Time Pattern Recognition Based Myoelectric Control Usability Study Implemented in a Virtual Environment," in *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug. 2007, pp. 4842–4845.
[16] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Medical Engineering & Physics*, vol. 21, no. 6, pp. 431–438, Jul. 1999.
[17] G. Kanitz, C. Cipriani, and B. B. Edin, "Classification of Transient Myoelectric Signals for the Control of Multi-Grasp Hand Prostheses," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 9, pp. 1756–1764, Sep. 2018.
[18] M. Stachaczyk, S. F. Atashzar, S. Dupan, I. Vujaklija, and D. Farina, "Multiclass Detection and Tracking of Transient Motor Activation based on Decomposed Myoelectric Signals," in *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, Mar. 2019, pp. 1080–1083.
[19] D. Farina, I. Vujaklija, R. Brånemark, A. M. J. Bull, H. Dietl, B. Graimann, L. J. Hargrove, K.-P. Hoffmann, H. H. Huang, T. Ingvarsson, H. B. Janusson, K. Kristjánsson, T. Kuiken, S. Micera, T. Stieglitz, A. Sturma, D. Tyler, R. F. ff Weir, and O. C. Aszmann, "Toward higher-performance bionic limbs for wider clinical use," *Nature Biomedical Engineering*, pp. 1–13, May 2021.
[20] C. Castellini, R. M. Bongers, M. Nowak, and C. K. van der Sluis, "Upper-Limb Prosthetic Myocontrol: Two Recommendations," *Frontiers in Neuroscience*, vol. 9, 2016.
[21] D. Yeung, I. Mendez Guerra, I. Barner-Rasmussen, E. Siponen, D. Farina, and I. Vujaklija, "Co-adaptive control of bionic limbs via unsupervised adaptation of muscle synergies," *IEEE Transactions on Biomedical Engineering*, pp. 1–1, 2022.
[22] J. M. Hahne, F. Biebmann, N. Jiang, H. Rehbaum, D. Farina, F. C. Meinecke, K.-R. Muller, and L. C. Parra, "Linear and Nonlinear Regression Techniques for Simultaneous and Proportional Myoelectric Control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 2, pp. 269–279, Mar. 2014.
[23] J. M. Hahne, M. Markovic, and D. Farina, "User adaptation in Myoelectric Man-Machine Interfaces," *Scientific Reports*, vol. 7, no. 1, p. 4437, Jun. 2017.
[24] A. Ameri, M. A. Akhaee, E. Scheme, and K. Englehart, "Regression convolutional neural network for improved simultaneous EMG control," *Journal of Neural Engineering*, vol. 16, no. 3, p. 036015, Jun. 2019.
[25] M. Ison and P. Artemiadis, "Proportional Myoelectric Control of Robots: Muscle Synergy Development Drives Performance Enhancement, Retainment, and Generalization," *IEEE Transactions on Robotics*, vol. 31, no. 2, pp. 259–268, Apr. 2015.
[26] A. Krasoulis, S. Vijayakumar, and K. Nazarpour, "Effect of User Practice on Prosthetic Finger Control With an Intuitive Myoelectric Decoder," *Frontiers in Neuroscience*, vol. 13, 2019.
[27] D. M. Hawkins, "The Problem of Overfitting," *Journal of Chemical Information and Computer Sciences*, vol. 44, no. 1, pp. 1–12, Jan. 2004.
[28] M. Ison, I. Vujaklija, B. Whitsell, D. Farina, and P. Artemiadis, "High-Density Electromyography and Motor Skill Learning for Robust Long-Term Control of a 7-DoF Robot Arm," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 4, pp. 424–433, Apr. 2016.
[29] S. Muceli and D. Farina, "Simultaneous and Proportional Estimation of Hand Kinematics From EMG During Mirrored Movements at Multiple Degrees-of-Freedom," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 3, pp. 371–378, May 2012.
[30] M. Nowak, I. Vujaklija, C. Castellini, and D. Farina, "Highly Intuitive 3-DOF Simultaneous and Proportional Myocontrol of Wrist and Hand," in *In Press*, Oct. 2020, p. 2.
[31] D. Farina, R. Merletti, and R. M. Enoka, "The extraction of neural strategies from the surface EMG," *Journal of Applied Physiology*, vol. 96, no. 4, pp. 1486–1495, Apr. 2004.
[32] L. H. Smith, T. A. Kuiken, and L. J. Hargrove, "Linear regression using intramuscular EMG for simultaneous myoelectric control of a wrist and hand system," in *2015 7th International IEEE/EMBS Conference on Neural Engineering (NER)*, Apr. 2015, pp. 619–622.
[33] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 848–854, Jul. 2003.

[34] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, and K. B. Englehart, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *Jama*, vol. 301, no. 6, pp. 619–628, 2009.

[35] A. J. Young, L. H. Smith, E. J. Rouse, and L. J. Hargrove, "Classification of Simultaneous Movements Using Surface EMG Pattern Recognition," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 5, pp. 1250–1258, May 2013.

[36] D. Sierra González and C. Castellini, "A realistic implementation of ultrasound imaging as a human-machine interface for upper-limb amputees," *Frontiers in Neurorobotics*, vol. 7, 2013.

[37] A. Gijsberts, R. Bohra, D. Sierra González, A. Werner, M. Nowak, B. Caputo, M. A. Roa, and C. P. D. Castellini, "Stable myoelectric control of a hand prosthesis using non-linear incremental learning," *Frontiers in Neurorobotics*, vol. 8, 2014.

[38] G. K. Patel, C. Castellini, J. M. Hahne, D. Farina, and S. Dosen, "A Classification Method for Myoelectric Control of Hand Prostheses Inspired by Muscle Coordination," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 9, pp. 1745–1755, Sep. 2018.

[39] M. Nowak and C. Castellini, "The LET Procedure for Prosthetic Myocontrol: Towards Multi-DOF Control Using Single-DOF Activations," *PLOS ONE*, vol. 11, no. 9, p. e0161678, Sep. 2016.

[40] M. Barsotti, S. Dupan, I. Vujaklija, S. Došen, A. Frisoli, and D. Farina, "Online Finger Control Using High-Density EMG and Minimal Training Data for Robotic Applications," *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 217–223, Apr. 2019.

[41] I. Strazzulla, M. Nowak, M. Controzzi, C. Cipriani, and C. Castellini, "Online Bimanual Manipulation Using Surface Electromyography and Incremental Learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 3, pp. 227–234, Mar. 2017.

[42] M. Nowak, T. Eiband, E. Ruiz Ramírez, and C. Castellini, "Action interference in simultaneous and proportional myocontrol: Comparing force- and electromyography," *Journal of Neural Engineering*, vol. 17, no. 2, p. 026011, Mar. 2020.

[43] T. R. Farrell and R. F. Weir, "The Optimal Controller Delay for Myoelectric Prostheses," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, no. 1, pp. 111–118, Mar. 2007.

[44] F. Cordella, A. L. Ciancio, R. Sacchetti, A. Davalli, A. G. Cutti, E. Guglielmelli, and L. Zollo, "Literature Review on Needs of Upper Limb Prosthesis Users," *Frontiers in Neuroscience*, vol. 10, 2016.

[45] H. Rehbaum, N. Jiang, L. Paredes, S. Amsuess, B. Graimann, and D. Farina, "Real time simultaneous and proportional control of multiple degrees of freedom from surface EMG: Preliminary results on subjects with limb deficiency," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug. 2012, pp. 1346–1349.

[46] S. Muceli, N. Jiang, and D. Farina, "Extracting Signals Robust to Electrode Number and Shift for Online Simultaneous and Proportional Myoelectric Control by Factorization Algorithms," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 3, pp. 623–633, May 2014.

[47] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "The Target Achievement Control Test: Evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses," *The Journal of Rehabilitation Research and Development*, vol. 48, no. 6, p. 619, 2011.

[48] J. Ryu, W. P. Cooney, L. J. Askew, K.-N. An, and E. Y. Chao, "Functional ranges of motion of the wrist joint," *The Journal of Hand Surgery*, vol. 16, no. 3, pp. 409–419, May 1991.

[49] A. P. Field, J. Miles, and Z. Field, *Discovering Statistics Using R*. London ; Thousand Oaks, Calif: Sage, 2012.

[50] W. H. Finch, J. E. Bolin, and K. Kelley, *Multilevel Modeling Using R*. New York: Crc Press, 2019.

[51] T. A. Snijders and R. J. Bosker, *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. Sage, 2011.

[52] D. A. Powers, "Multilevel models for binary data," *New Directions for Institutional Research*, vol. 2012, no. 154, pp. 57–75, 2012.

[53] C. J. Anderson, J.-S. Kim, and B. Keller, "Multilevel Modeling of Categorical Response Variables," 2014, p. 39.

[54] A. Pradhan, N. Jiang, V. Chester, and U. Kuruganti, "Linear regression with frequency division technique for robust simultaneous and proportional myoelectric control during medium and high contraction-level variation," *Biomedical Signal Processing and Control*, vol. 61, p. 101984, Aug. 2020.

[55] C. Igual, L. A. Pardo, J. M. Hahne, and J. Igual, "Myoelectric Control for Upper Limb Prostheses," *Electronics*, vol. 8, no. 11, p. 1244, Nov. 2019.

[56] C. Amma, T. Krings, J. Böer, and T. Schultz, "Advancing Muscle-Computer Interfaces with High-Density Electromyography," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, ser. CHI '15. New York, NY, USA: Association for Computing Machinery, Apr. 2015, pp. 929–938.

[57] M. Rojas-Martínez, M. Mañanas, J. Alonso, and R. Merletti, "Identification of isometric contractions based on High Density EMG maps," *Journal of Electromyography and Kinesiology*, vol. 23, no. 1, pp. 33–42, Feb. 2013.

[58] M. Connan, R. Kõiva, and C. Castellini, "Online Natural Myocontrol of Combined Hand and Wrist Actions Using Tactile Myography and the Biomechanics of Grasping," *Frontiers in Neurorobotics*, vol. 14, p. 11, Feb. 2020.

Publication 3 Applying Radical Constructivism to Machine Learning: A Pilot Study in Assistive Robotics

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Applying Radical Constructivism to Machine Learning

A Pilot Study in Assistive Robotics

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> Context • In this article we match machine learning (ML) and interactive machine learning (iML) with radical constructivism (RC) to build a tentative radical constructivist framework for iML; we then present a pilot study in which RC-framed iML is applied to assistive robotics, namely upper-limb prosthetics (myocontrol). **> Problem** • Despite more than 40 years of academic research, myocontrol is still unsolved, with rejection rates of up to 75%. This is mainly due to its unreliability – the inability to correctly predict the patient's intent in daily life. **> Method** • We propose a description of the typical problems posed by ML-based myocontrol through the lingo of RC, highlighting the advantages of such a modelisation. We abstract some aspects of RC and project them onto the concepts of ML, to make it evolve into the concept of RC-framed iML. **> Results** • Such a projection leads to the design and development of a myocontrol system based upon RC-framed iML, used to foster the co-adaptation of human and prosthesis. The iML-based myocontrol system is then compared to a traditional ML-based one in a pilot study involving human participants in a goal-reaching task mimicking the control of a prosthetic hand and wrist. **> Implications** • We argue that the usage of RC-framed iML in myocontrol could be of great help to the community of assistive robotics, and that the constructivist perspective can lead to principled design of the system itself, as well as of the training/calibration/co-adaptation procedure. **> Constructivist content** • Ernst von Glasersfeld's RC is the leading principle pushing for the usage of RC-framed iML; it also provides guidelines for the design of the system, the human/machine interface, the experiments and the experimental setups.
> Key words • **Machine learning, interactive machine learning, radical constructivism, assistive robotics, human-machine interaction, co-adaptation.**

Introduction

« 1 » According to Arthur Samuel (1959), *machine learning* (ML from now on) is "the subfield of computer science that […] gives computers the ability to learn without being explicitly programmed." Can radical constructivism say something useful about machine learning, something which would enrich its capabilities, our understanding of it, and possibly shed light on learning *tout court?*

« 2 » First of all, what is machine learning? For the benefit of those readers starting from a realist perspective, let us look at it, at least initially, using a realist language. Samuel's definition is to some extent correct: indeed, ML is an "explicit program," since it runs on computers, and today's computers must still be programmed in the old-fashioned way; but it is a program that observes statistical regularities in the world and matches them against one another.

« 3 » As a direct consequence of this, the output of ML will sometimes not match our expectations, i.e., "it will do the wrong thing," and not as the result of a bug. This, as a realist statistician would put it, "is due to the uncertainty inherent to statistics – one can never be statistically sure that something is true." Or, as a hypothetical realist (the most common sub-type of realism among the ML community) would put it: "statistical truth is only true most of the times." Therefore, a program that searches for statistical similarities in the world will now and then, e.g., deem as similar two things which the researcher defines as not belonging to the same category, and vice versa. This is correct and must be accepted, as opposed to bugs in standard programming, which are always bad and must be eliminated.

« 4 » The only way to "debug" an ML program is to show it more exemplary regularities – to "teach" it something more about the world – to enrich its own model of how the world works – to help it to better organise its own private world according to the researcher's idea of the world.

« 5 » More concretely, ML builds a mathematical function (a "model" from now on) approximating the observable behavior of some variables of an unknown process of interest, given some very basic restrictions on the shape of the model itself, and a set of examples – a set of input data (values of the variables) and corresponding target values to which each datum is associated, sampled from the process itself. This set represents the regularities so far observed during the past behavior of the process. The model, which compactly represents them, can be used to predict the future behavior of the process (an excellent introductory text is Shalev-Shwartz & Ben-David 2014).

« 6 » For instance, an ML model can be built using a set of images acquired from a street camera and corresponding (face-yes/face-no) values, denoting whether an image contains a human face or not. After the model has been built, will it correctly identify new images as containing/not containing a face? Another example: an ML model of the temperature of the Mediterranean Sea can be built using a set of temperature values and the times at which they were observed. Will the temperature of the Mediterranean at specific future times be correctly predicted by the model?

« 7 » Mathematically speaking, the model is built by minimising a cost functional associated to the examples. It is an *optimal fit* of the examples, naturally endowed with the ability to both compactly explain the past target values for each known input datum, and to approximate target values associated with so-far-unseen input data. The model is therefore an attempt to "make sense" of the examples, to "organise" them, to use them in order to predict the future behavior of the process.

« 8 » It obviously follows that the quality of the model (its predictive power) depends on how much the samples collected so far are representative of the behavior of the process both in the past and in the future. So, the answer to the questions posed in §6 is "yes, *provided that a good set of examples was collected in the beginning.*"

« 9 » Notice that the minimisation of a cost functional is a completely mechanical procedure; moreover, no *a priori* physical knowledge about the process to be modelled is, in principle, required – only the ability to draw examples from it. In this sense, an ML model is indeed a machine that "learns without being explicitly programmed" – a softer, perhaps more flexible way of telling our computers what to do, than programming. And the idea is a winning one: ML has recently (at least to some remarkable extent) solved problems that were considered beyond the reach of computers, e.g., form detection in pictures, automated medical diagnosis, speech recognition, content analysis of a text, the game of *Go*, etc. So far, so good.

Is machine learning a radical constructivist business?

« 10 » A great deal of the research in ML seems to suffer from a methodological weakness: machine learning tends to be used as a number-crunching black box, at which to throw as many examples as possible, hoping that it will yield a usable relationship between input data and target values. Too often, scarce attention is paid to the quality, the origin and the meaning of the examples (e.g., Wagstaff 2012). Moreover, examples are considered to be "the reality," rather than being considered artefacts manufactured by the researcher's explicit or implicit choices. The whole procedure suffers from an insufficient awareness of the epistemological problem.[1]

« 11 » This weakness stems, in our opinion, from a widespread *realist* attitude to knowledge and learning, in statistics in general and in ML in particular. A "realist statistician," we can say, assumes that "there is a world out there" and that "we can build a real, even if somewhat rough, model of this world." Once such a model is built, no further changes are needed. In the case of ML, the example set represents knowledge about the world out there, given at the beginning of time, used to predict the future evolution of the target process.

« 12 » In one sentence, ML is so far prevalently *a realist love affair,* for *realist statisticians.* But even a realist statistician (and those who adopt some form of realism) *may* observe that there are indeed many cases in which *this attitude will fail;* in particular, it will fail whenever too few examples are available, e.g., because they are expensive to collect, or if the process of interest is non-stationary, implying that the examples collected at the beginning of time will at some point no longer represent its behavior.

« 13 » Thus, we propose to shift the attitude to ML from realist to *radical constructivist,* as radical constructivism (RC from now on) is defined by Ernst von Glasersfeld (e.g., Glasersfeld 1983, 1995).

« 14 » There are at least four remarks suggesting such a change in paradigm to a realist ML researcher.

« 15 » *In the first place,* let us notice that if we strip the concept of ML to the bare bones, all we are left with (§5) is an agent that tries to *organise perceptual objects*, obtained through specific sensory channels, as best as it can. No physical, chemical, mathematical, ontological, …, knowledge about the process of interest is required. This means that in ML, no knowledge of "external reality" need be assumed. ML deals only with "perceptual" data. This is a very radical-constructivist concept (Glasersfeld 1995: 58f) that we call in short "the construction of experiential reality."

« 16 » *In the second place,* ML is about *matching "perceptual" patterns* – finding regularities among subsets of examples, compactly representing these regularities and using them to predict new target values (§5 again). That is what an ML model does.[2] Not incidentally, matching perceptual patterns is also one of the foundations of RC: "learning as a constructive activity" (Glasersfeld 1983).

« 17 » *Thirdly,* consider again the realist attitude to ML (§11): as opposed to the realist statistician, for the RC statistician indeed "there is a world out there," but as well "we cannot build a *real* model of this world – we can only build a viable representation of it (one of the many possible), useful to do something specific in it" (utilitarianism) *and* in agreement with our pre-conceptions of this world (conceptual coherence). We are continually forced to test the viability of this representation, for our specific purposes and according to our pre-knowledge, through our interaction with the world. The value of an idea of the world is measured in term of fitness to achieve a specific goal *and* (better) fitness against other ideas the subject has about the world, not in term of the correspondence between the idea and a mind-independent reality (Glasersfeld 1995: 68f). We say in this case, that viability is *utilitarianism* plus *conceptual coherence.*

« 18 » *Fourthly*, "pre-knowledge and learning." The realist attitude to ML assumes that knowledge is free from pre-knowledge. The radical-constructivist attitude, as opposed to that, contends that knowledge –

1| Deep learning coupled with big data represents an unfortunate push in this very direction, albeit a very successful one from a practical point of view.

2| Actually, *pattern matching* or *pattern recognition* is the old umbrella term for ML.

every possible segmentation of the perceptive field – depends on, and is shaped by, the subject's *pre-definition of what can be seen in the perceptive field*, and that this pre-definition is shaped, in turn, by the interaction the subject has had with the others and with the world (learning). Furthermore, according to RC, the subject does not interact *with the other* (and the other's signals), but only and exclusively *with her perception of the other* (and of the other's signals) and with her previous personal ideas of the other and of the world, since human beings cannot access the "real world" (a mind-independent reality) but only *their perception of the world.* This is a very different model of interaction from the realist one

« 19 » Particularly, during interaction with the others, the subject

a recognizes a specific situation according to her memorized "schemata,"
b performs a specific activity associated with the situation, and
c checks her own specific expectations that that activity should produce a specific previously experienced result.

If this does not happen, the subject is *perturbed* and forced to review her initial sensory elements to find a new structure in these sensory elements and eliminate the perturbation. *All* these processes are presumed to be *subjective* and *internal* to the cognizing agent (again, Glasersfeld 1995: 68f). So, an ML engineer will endow her ML system with an initial simple set of schemata (pre-education) and an engine to apply these schemata, having expectations, possibly to be disconfirmed, and trying to reshape her *sensory material* (learning). This actually is, and we can call it in short, "von Glasersfeld's learning theory."

« 20 » Therefore, an RC statistician engaged in ML would, as opposed to her realist colleague,

a collect examples according to her cultural pre-conception of the world,
b build a temporarily viable model of the world – *viable* according to her own explicit or implicit goals and pre-assumptions/pre-definitions of the world,
c have expectations and check how well the model works, and if the response is not good, she would
d try to reorganize the examples and/or collect new ones, with which to update the model – go back to step (a).

From a (realist) engineer's perspective, this endless loop aims at countering the potential non-stationarity of the process to be modelled.

« 21 » From what we have said so far, it almost appears as if ML already were an RC business. In order to complete the picture though, we also need to enforce the loop outlined in §§19f – we need the ability to *have expectations and update the model at any time,* specifically whenever it does no longer reflects the expectations about the underlying process or the system's goals – whenever its predictive power has become unsatisfactory. Updating a model means changing it in order for it to accommodate old and new knowledge – to accommodate new examples, gathered on demand without the need to obliterate all past knowledge. (Notice that sometimes some of the past knowledge *must* be forgotten, but it is essential not to be *forced* to forget it upon updating!) Model updates must be triggered by some kind of feedback from the world confirming or perturbing the model, perhaps an external agent, able to judge the model's current performance, on the basis of some well-defined purpose.

« 22 » Although little practiced (and even less theoretically studied) in ML literature, this idea already exists and is called, not incidentally, *interactive machine learning* (iML from now on). iML adds to standard ML the possibility of being helped by an external agent, recognising that the predictive power of the current model has become insufficient, and that a new data gathering and model update is required. iML, so far, has been tested in conditions that are particularly hard for standard ML, such as recognising the presence of complex structures in an image: whenever the model failed to correctly categorise an image, a human operator would weigh in, give the system a further example, and request a model update.

« 23 » Interestingly, iML has recently been linked to (non-radical) constructivism by Adavait Sarkar, who claims that

> "the interaction loop of interactive machine learning systems facilitates constructivist learning, as it maximises the interaction between the end-user's experience of the model, and their ideas regarding the model status." (Sarkar 2016: 1472)

However, this is, to the best of our knowledge, the only case so far in which these two fields have talked to each other. This, although iML has been used and implicitly defined in a number of cases (for instance, in Fails & Olsen 2003; Iturrate et al. 2015; Strazzulla et al. 2017). Some recently revamped ML approaches, e.g., recurrent neural networks, can even be viewed as "interactive in nature"; to the best of our knowledge, however, a coherent conceptual framework about interactivity (e.g., the RC's learning theory) in ML is still missing, and this is where RC can help.

« 24 » Ipractice, interactivity is enforced through *incrementality*. An incremental ML system is precisely an ML system that allows for updating/downdating its current model. The good news is that, in principle, any standard ML system can easily be turned into an incremental one by keeping the examples seen up to now, and whenever a model update is (somehow) triggered, adding the new examples to the old ones, selecting the examples of interest from the new example set, and then re-building the model from scratch using the selected examples only.[3]

« 25 » To some extent iML, as enforced so far in literature, already smells like RC; but this generally remains an intuition of the researcher – there is no adoption of a theory of knowledge and learning as RC. It is *interaction* conceived as a realist scientist can conceive it (sometime as an anti-theoretical scientist can conceive it). Actually, through the interaction, the iML system, in the intention of a realist scientist, builds a "true" model of reality (this way bypassing the problem of a changing reality) simply by "adding input data." We claim that adding to this an epistemological awareness and a more robust learning theory, as offered by RC, will open new paths of research and technological improvement.

« 26 » Our argumentation shows that in the end it will be useful to adopt an RC-framed iML. The tentative framework we sketched above is an attempt at opening a discussion between the RC community and the ML community to enrich our idea of RC-framed iML.

3| This solution can be computationally/memory intensive but there are ways around the problem in the majority of the cases of interest.

Radical constructivist machine learning in action

« 27 » This new point of view of an RC-framed iML raises the question: what is it useful for? An immediate, almost trivial idea (also inspired by the definition of iML in §§22f), is that *human-machine interaction* should be the typical problem area in which ML, and iML, can be empowered by RC.

« 28 » A second, perhaps less immediate way of empowering ML with RC consists in empowering the statistical analytical tools behind ML with the ideas outlined in §§15f, e.g., giving the ML system a "set of schemata" (a sort of "culture"), some pre-selectors to segment its perceptive field, to pre-treat/pre-interpret the information it will crunch and match (to have some "expectations" on the world and the possibility of being "perturbed"). We can call this pathway "crunch *before* match."[4]

« 29 » We talk about human-machine interaction whenever a human subject must guide, teach, control a machine (a robot, a computer, a virtual avatar, etc.) that is endowed with only limited autonomy (Card, Newell & Moran 1983). Here, the standard ML tools at the disposal of the engineer usually fail since, for the machine, modelling human behavior is extremely hard; nevertheless, it is needed to some extent, if one wants to detect the subject's intent, that is, what the subject wants the machine to do. Human behavior is non-stationary, complex, culture- and goal-directed, almost unpredictable in the medium and long run; plus, usable examples from humans can be excruciatingly hard to obtain. All these aspects make the problem of human-machine interaction extremely hard for "realist" ML.

« 30 » So, what is needed in human-machine interaction is a way to constantly "monitor" the desires of the subject, continually gather new examples and learn from her, engage her in a dialog with the expectations of the ML system – the perfect problem for an RC-framed iML system. In addition, in this field we have the almost obvious chance to exploit the judgment of the human as the feedback system/external agent ("the world talks back to the *knowing machine*") mentioned in §§21f, to trigger the perturbation and the model updates (Castellini 2016). The match with the RC concepts of assimilation, scheme theory, accommodation, and equilibration is hereby clear: the ML system must have the capability to be perturbed and to re-equilibrate the perturbation produced by the interaction with the world into its model of the world/of human intent.

« 31 » We claim that RC-framed iML could be a more useful/interesting/sophisticated choice than traditional ML and iML, and especially so whenever dealing with "feedback" in human-machine interaction.

« 32 » We have arrived at this idea in a somehow non-linear way. Namely, the need for iML in human-machine interaction stems from the frustration of the second author of this article, an engineer who has been trying for 10 years to build smart prosthetic arm/hand control systems *(upper-limb myocontrol),* which is a typical case of human-machine interaction. Unhappy with ML-based myocontrol, he recently tried to evolve ML pursuing "a more interactive pathway" (Castellini 2016); while doing so, he faced a new set of problems which called for appropriate conceptual tools. The encounter with the third author of this article, a trained RC psychologist dealing with decision-making models and decision-support systems in the subfield of investing, resulted in the usage of the concepts of *knowledge, learning, communication,* and *feedback* as traditionally developed within RC.

« 33 » Upper-limb myocontrol (Fougner et al. 2012) consists of using muscle activation of the remaining upper limb of an amputated human subject to detect her intention to move and accordingly control a prosthetic arm/hand to perform the desired action quickly, precisely, safely and reliably – in this case ML is used to transform such activity (input data) into control commands (target values). Most such systems are, currently, realist ML systems: a great deal of arm/hand/muscle configurations are gathered initially, a model is built, then its accuracy is tested while the amputated subject tries to control the prosthesis. The few exceptions (e.g., Gijsberts et al. 2014; Hahne, Markovic & Farina 2017; Mathewson & Pilarski 2017) are proving to work in practice. The only commercial solution enforcing ML, namely the *Complete Control* system by CoApt LLC, employs iML in the form of the option to "re-calibrate" the prosthetic control system whenever the user so wishes (Lock et al. 2011; Simon, Lock & Stubblefield 2012; also, personal communication by Blair Lock, CEO of CoApt LLC, 2017).

« 34 » The traditional realist approach to myocontrol still fails after 40 years of research (Jiang et al. 2012; Farina, Jiang & Rehbaum 2014), the main problem being *unreliability:* the inability to guarantee that an arm prosthesis will do exactly what the subject wants, for exactly the length of time she wants. Unreliability can be catastrophic (e.g., prosthetic hand unwantedly releasing the steering wheel while driving) or in the best case "just" frustrating, humiliating and socially unacceptable. As a consequence of this impasse, the acceptance of self-powered prostheses by upper-limb amputees is very limited, with rejection rates of up to 75%. Simply put, state-of-the-art upper-limb prostheses do not work well enough to justify the cost and effort required to use them (Micera, Carpaneto & Raspopovic 2010; Peerdeman et al. 2011; Castellini et al. 2014).

« 35 » Our goal is to show that RC-framed iML could change the situation. Unreliability arises from the innumerable variety of different situations in which a prosthesis must perform a certain action. For instance, maintaining a firm grasp on a rail must be ensured notwithstanding external force disturbances, changes in applied muscle activation, the posture of the arm, etc. Since it is *de facto* impossible to build an example set, at the outset, containing examples of all these situations and all further possible ones, sooner or later realist ML-based myocontrol will fail (Castellini 2016). A spectacular example of this is represented by the outcome of the ARM competition of the 2016 *Cybathlon* – see, e.g., Wolf Schweitzer, Michael Thali & David Egger (2018) for a detailed analysis of the current pitfalls and practical requirements of myocontrol.

« 36 » As opposed to that, existing iML-based myocontrol counters this problem ex-

4| What statistical analysis can gain by adopting the RC perspective – how the "maths" can be used differently – is a very interesting research agenda for the future; notice that nowadays the ML community "teaches a culture or schemata to the system" by choosing an ML algorithm specific to each different task the ML system needs to pursue.

actly thanks to on-demand model updating: whenever a new situation arises in which it fails, the subject "teaches" the system how to cope with it; the system, in turn, readily adapts to the new knowledge (Castellini 2016). Unsurprisingly, iML-based myocontrol already is reported by, at least, Arjan Gijsberts et al. (2014) and Ilaria Strazzulla et al. (2017), where, however, very little is said about the most proficient/natural way to design and enforce the interaction between the system and the user. Another crucial aspect or side-product of iML, namely co-adaptation, is only now being explored (Hahne, Markovic & Farina 2017), yet there is no indication of what theoretical framework could/would optimally guide the design of the interaction interface.

« 37 » Is our claim that RC-framed iML is superior when dealing with "feedback" in human-machine interaction (§31) justified, specifically as far as upper-limb myocontrol (§35) is concerned? Does RC-framed iML enforce better myocontrol than realist ML? This is a subset of our RC research agenda: "Can a knowing subject (here an ML system) that adopts *a non-realist theory of knowledge* do better than a realist one?" To shed some light on this question we have compared an RC-framed iML-based myocontrol system with a traditional ML-based myocontrol system in a pilot experiment involving human subjects.

Experiment

Overview

« 38 » Ideally, two upper-limb myocontrol systems, an RC-framed and interactive one and a non-interactive (RC versus realist) one would be compared during completely unrestricted daily-living usage by two distinct groups of amputated subjects. Here we adopted some simplifications. Firstly, we engaged fifteen intact human subjects only; secondly, we used two 3D hand models displayed on a computer screen instead of tangible prosthetic devices.

« 39 » The experiment as a whole consisted of three sub-experiments, each of which will be from now on referred to as Experiment 0, 1 and 2, respectively. Namely, we compared (Experiment 0) a traditional, non-interactive, *realist* upper-limb myocontrol ML system, with (Experiment 1) a "part-time" RC-framed interactive ML system, a "weakly RC" system, and (Experiment 2) a "full-time" RC-framed interactive ML system, a "fully-fledged" RC system.

ML method

« 40 » Following the motto "keep it as simple as possible, but not simpler than that," attributed to Albert Einstein, all three ML systems employed in the experiment are based upon least-squares regression in the regularised form called *Ridge Regression*, filtered through a non-linear mapping called *Random Fourier Features* (RR-RFF). RR-RFF exists both in "batch" form (i.e., non-incremental and therefore non-interactive) and in incremental form (iRR-RFF – for the mathematical details see Castellini 2016). Notice that iRR-RFF is guaranteed to yield the same optimal model as RR-RFF, whenever the same example sets are used with either method. This enables a fair comparison between an ML and an RC-framed iML system even from an exquisitely mathematical point of view.

Participants

« 41 » Fifteen intact human subjects (5 females and 10 males, age 19–54 years) participated in the experiment. Before the experiment took place, it was clearly explained to each participant, both orally and in writing, that no health risk was involved. Each participant signed an informed consent form. The experiment was previously approved by the internal committee for data protection of the Institution where the experiments took place, and it followed the guidelines of the World Medical Association Declaration of Helsinki. The participants were randomly assigned to one experiment only, so that five participants took part in each experiment.

Experimental setup

« 42 » The experimental setup was common to all three experiments, and consisted of

- a *Myo* bracelet by Thalmic Labs,
- two 3D hand models displayed on a computer screen, and
- a simple voice reproduction/speech recognition system.

« 43 » The Myo bracelet (https://www.thalmic.com) consists of eight uniformly spaced sensors, able to detect the electromyographic signal generated by the muscle activity of the subject's forearm.

« 44 » The 3D hand models realistically mimic the motions of a human wrist and hand. One of the models is white while the other is rendered in skin-like texture; the former (from now on referred to as *the stimulus*) is used to provide visual stimuli to the participants, i.e., it is controlled by the software itself; whereas the latter (from now on referred to as *the prosthesis*) simulates the prosthesis – given the current model, it enforces the predicted motions of the hand and wrist, as evaluated from the data provided by the bracelet.

« 45 » The speech recognition and synthesis system is the one embedded in Microsoft.NET Framework 4.5, able to distinguish a small set of words (in this case, "good"/"bad") pronounced by the subjects, and to utter predefined voice messages, which we configured with a clearly synthetic female voice. All sentences were uttered in the first person and address the participant in the second person (e.g., "you are now going to teach me how I should move").

Experimental protocol

« 46 » Each participant sat comfortably in front of the computer screen, and the bracelet was wrapped around her forearm. She was instructed to hold the forearm vertically, leaning the elbow on the table.

« 47 » A voice message was played. The prosthesis "spoke," explaining to the subject that the "*training session*" (the experiment) was about teaching it – a new kind of hand/wrist prosthesis able to learn – how to properly perform the movements intended by the participant, and that to this aim, a 3D hand model would eventually appear on the screen, representing itself (the prosthesis). The prosthesis *clearly stated* that the participant would not be judged on her performance, but rather that she was going to "show" the prosthesis how each single movement was to be performed, by simply doing it; rather, the prosthesis was to be judged by the participant on its learning ability. Particular care was taken by the prosthesis in asking the participant to be patient and not to get disappointed if it did not correctly ex-

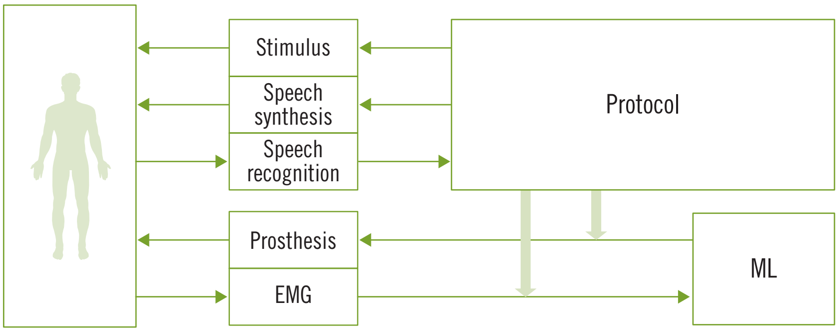

Figure 1 • A schematic depiction of the experimental setup. Subjects interact with the protocol controller via speech recognition, speech synthesis, and by looking at a PC screen on which the stimulus is displayed. The ML method "converts" EMG signals into live configurations of the prosthesis to be shown as well to the subject; while the protocol controller establishes what to display and utter, and when to open/close the flow of information between the subject and the ML method. The protocol controller, together with the ML method, constitute a flexible framework for all three experiments, allowing for different levels of interactivity.

ecute the required task. After all, concluded the prosthesis, its learning ability was "only in its infancy."

« 48 » We chose this way to communicate to the subject what to do in the experiment, to try and build a psychological context of interaction rules and reciprocal roles, potentially inducing in the subject the construction of positive "emotions" (Harré 1986) toward the "learning" prosthesis. More generally, while designing the experimental protocol, we also tried to take into account the main criticisms raised by postmodern social psychology with regard to the way human subjects are treated in most experimental psychology (and in general in experiments involving human subjects), i.e., that experimenters neglect to offer to (co-construct with) the subject a semiotic definition of the experimental situation meaningful to her, and take into account the meaning of the experimental setting from their own perspective only (Gergen 1978a, 1978b, 1985; Gergen & Gergen 1985; Harré 1979; Harré, Smith & van Langenhove 1995). Figure 1 shows a schematic representation of the experimental setup.

Experiment 0

« 49 » Experiment 0 (the realist machine learning system) consisted of two phases that we will call model building (MB) and model testing (MT).

« 50 » At the beginning of MB, the stimulus was shown on the screen; the prosthesis then explained that "the white hand on the screen" (the stimulus) would now perform a series of hand and wrist movements (tasks), and that the participant should simply mimic what the stimulus was doing with her hand and wrist, as accurately as possible, in order to give the prosthesis a chance to "try and understand" what each movement looked like when seen through the signals it received from the bracelet.

« 51 » Soon afterwards, the stimulus was shown on the screen. A randomised sequence of 30 tasks (6 actions, each action repeated 5 times), was played by the stimulus. The actions were: no-action; wrist flexion; wrist extension; wrist pronation; wrist supination; and hand closing. No voice interaction was provided during this phase. MB would end at the end of this sequence.

« 52 » In this experiment, the ML system had, so to speak, the expectation that all signals it would receive would be "good" signals. *The system would experience no perturbation in the building of its inner vision of the "world."* In other words, each signal was "fitting" with previous signals, and the system was forced to accept all signals as good ones, upon which to build its own "reality" (model).

« 53 » In practice, the model was evaluated in the interval between MB and MT, using the data collected during MB. The evaluation took a few seconds, so that no apparent interruption would be felt by the participant.

« 54 » At the beginning of MT, the forearm of the participant would be hidden from view using an opaque cardboard partition (this is our rough approximation for the subject "wearing" the prosthesis); then the prosthesis would appear on the screen, beside the stimulus. It would then explain that now the stimulus would show a further series of tasks, similar to those that had appeared during MB, that the participant must reproduce those actions, and that the prosthesis would try to understand the signals it received from the bracelet and mimic the action performed by the participant as best it could.

« 55 » It also explained that, after each task had been performed, the prosthesis would verbally ask that the participant evaluate its performance; the participant would then be asked to say "good" or "bad" according to her own judgment.

« 56 » Soon afterwards, a further, randomised sequence of 90 tasks (the same 6 actions as during MB, but in this case each action was repeated 15 times) was played by the stimulus. After each task, the judgment would happen: the prosthesis would ask how it had performed, and the participant would answer "good" or "bad." Figure 2 shows a bird's eye view of the experimental setup while a subject was engaged in Experiment 0, MT.

Experiment 1

« 57 » Experiment 1 (the "part-time" interactive machine learning system) consisted of two phases like Experiment 0. In this case, however, the hand of the participant was hidden behind the cardboard partition already during MB, and the prosthesis would be immediately visualised beside the stimulus (the participants "wear" the prosthesis from the beginning). The same randomised sequence of tasks as in Experiment 0 was played by the stimulus; but in this case, after each task, the participant would be asked by the prosthesis to evaluate its own performance, just like during MT of Experiment 0.

« 58 » If the participant answered "good," the data gathered during the task was directly added to the machine-learning model in order to reinforce the positive result. If the participant answered "bad," she was vocally instructed to perform the task once again, and the data collected during this new instance of the action would be added to the model in order to correct for the previous negative performance. In both cases, the model would be immediately re-evaluated in order to reflect the new acquired data without delay. This way, assimilation and accommodation directly enter the picture of iML: via the external/human feedback.

« 59 » In this case, we can say, the ML system had the expectation that all signals it would receive would be "good" ones, but at the same time it would indeed experience some perturbation (the negative human feedback), so it was forced to not assimilate all signals, but rather to accommodate some specific ones, changing its recognition pattern and building a different scheme (model).

« 60 » MT in Experiment 1 was identical to MT of Experiment 0.

« 61 » Substantially, Experiment 1 consisted of *a partially interactive version of Experiment 0:* during MB, the participant would offer the prosthesis some confirmation and some perturbation, therefore helping the prosthesis to better learn the patterns corresponding to the required actions, so that in the end the model would reflect the corrections.

« 62 » Notice that the amount of data used to build the model in Experiment 1 was exactly the same as in Experiment 0 (30 tasks) – what changed was the added interaction with the participant, and consequently, the *possibility for the system to have confirmation or perturbation of its inner world* formed with the data gathered during MB.

Experiment 2

« 63 » Experiment 2 consisted of one phase only, identical to MB of Experiment 1, except that the stimulus would play a randomised sequence of 120 tasks (the same 6 actions as in the previous experiments, but in this case each action was repeated 20 times). As in Experiment 1, the model would be re-evaluated after each task (again, according to the "good"/"bad" judgement of the participant); but for each task, *data gathered during the past five repetitions only of this action were used to build the model.* This ensured that the amount of data used to build the model was, again, the same as in the previous experiments (30 tasks).

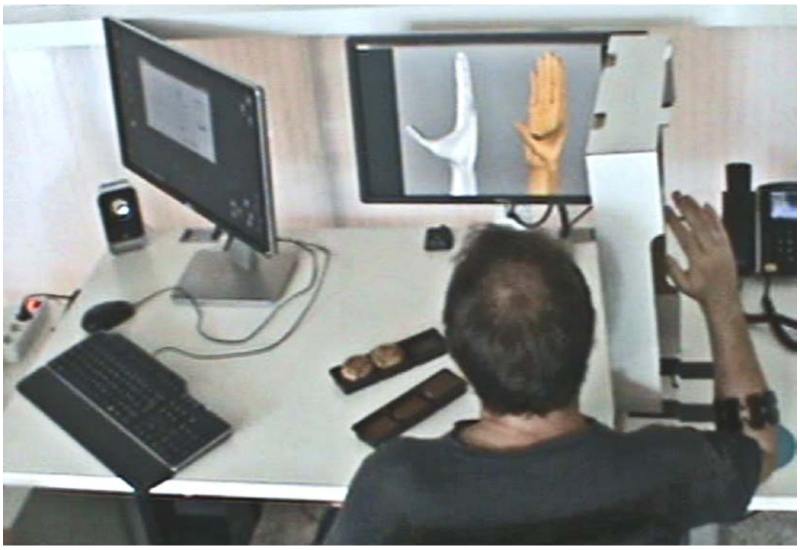

Figure 2 • The experimental setup while a subject performs Experiment 0, MT. The stimulus (white hand) and the "prosthesis" (skin-textured hand) are displayed on the screen; the subject's right arm (wearing the Myo bracelet) and hand are shielded from view using a cardboard partition.

« 64 » Experiment 2 consisted therefore of a "*continual learning/feedback*" *version of Experiment 1,* enforcing vocal interaction between the participant and the system at all times.

« 65 » According to the RC learning theory, our ML system *did* have a scheme of the world: it had indeed the expectation that all signals received would be "good" ones, but constantly experienced (*internal*) confirmation and perturbation, thus being forced to modify its own model of the world. The system designed for Experiment 2 is our main conceptual (and practical) attempt at arriving at iML via the RC theory of knowledge and learning, prevalently stressing the RC idea of viability relating to "utilitarianism" (see above, §17).

« 66 » Figure 3 graphically represents the three experiments, while Figure 4 shows flow-charts of each experiment.

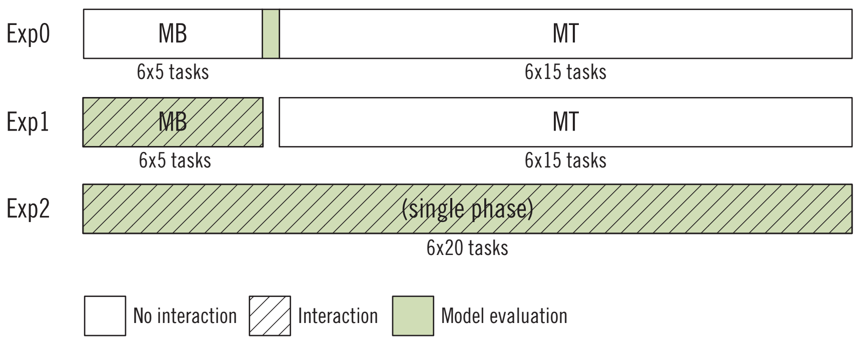

Figure 3 • A graphical representation of the three experiments. Phase MB (Model Building) of Experiment 1 and the entire Experiment 2 are interactive; model generation happens between phases MB and MT (Model Testing) in Experiment 0, during phase MB in Experiment 1 and during the entire experiment in Experiment 2.

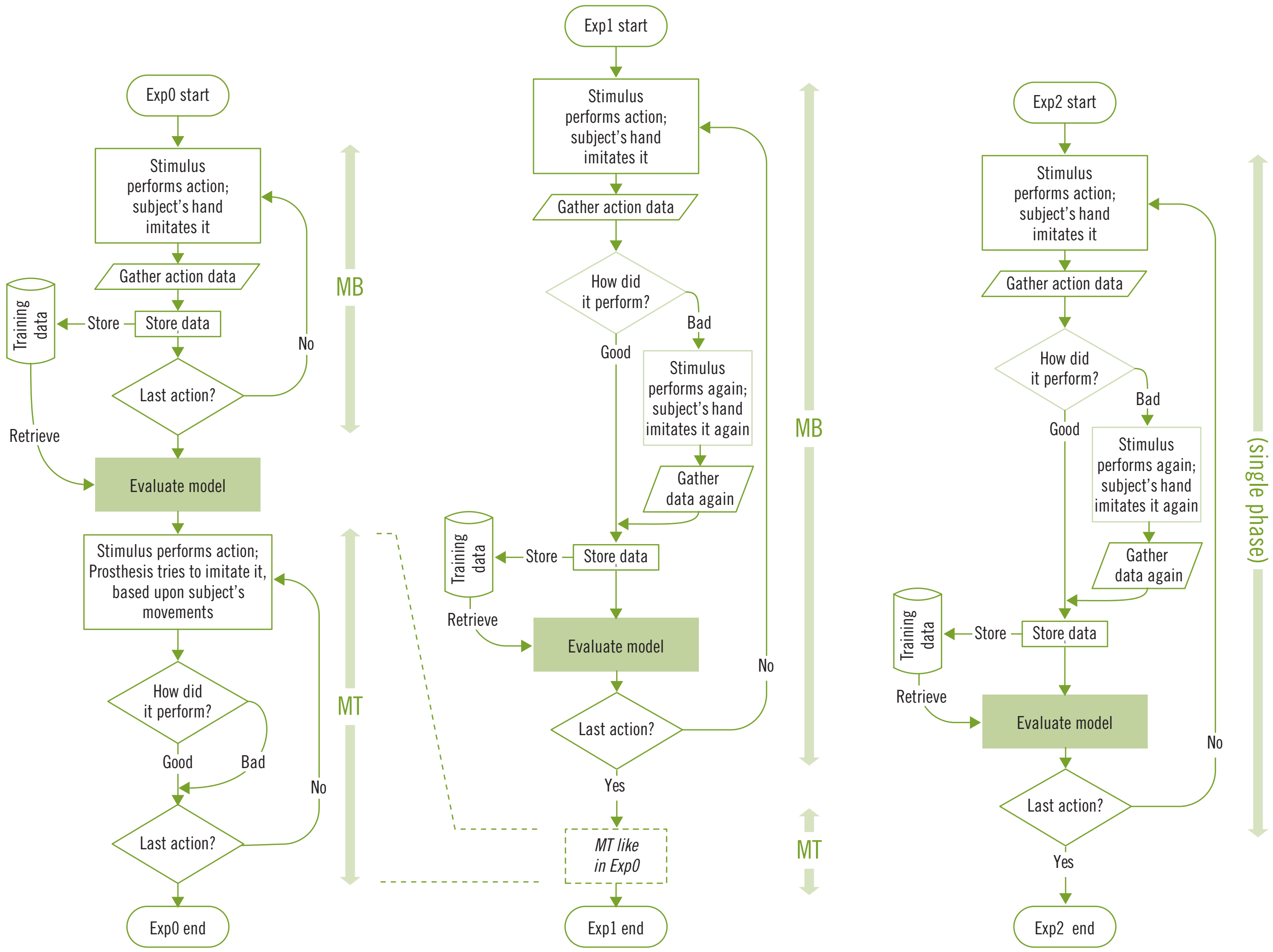

Figure 4 • Flow-charts of the three experiments (from left to right: Experiment 0, 1 and 2). Notice that the single phase in Experiment 2 is identical to MB in Experiment 1. Also notice that model evaluation happens only once during Experiment 0, whereas it happens within an interaction loop in Experiments 1 and 2.

Evaluation measures

« 67 » We wanted to measure which of the three machine learning systems (realist, "part-time" RC-framed interactive and "full-time" RC-framed interactive) could produce a model capable of better understanding the patterns produced by the subject, thereby properly performing (as a prosthesis) the actions that the subject wanted to do. So, we adopted a measure that was objective for the experimenter and the research community of upper-limb myocontrol: the normalised root-mean-squared error (nRMSE) between the position of the stimulus and that of the "prosthesis" during each task – essentially, the discrepancy between the desired position and what the prosthesis manages to do. To evaluate the nRMSE, for each task we considered the last second in which the stimulus was performing the required action, in order to neglect as far as possible any transition effect (i.e., the time the subjects needed to become aware of what was asked of them, and to move their own hand and wrist to the required position).

« 68 » We also wanted to measure which of the three machine learning systems was perceived as the best one by the subjects, so we also adopted a measure that was objective for the subject: the number of poor/good judgements expressed by the subject during the experiment.

« 69 » These two measures described in the two preceding paragraphs make our experimental evaluation akin to the Target Achievement Control test (TAC test, see, e.g., Simon et al. 2011), an assessment test well-known in the myocontrol community; the only remarkable difference is that whether a task is successful or not is left to the participant's judgment.

« 70 » Lastly, we wanted to evaluate the quality of the subject-prosthesis relationship from both the subject's and the machine's point of view – we were interested not only in measuring the performance, but also in checking the reciprocal adaptation. So, first of all we estimated how the signals of each

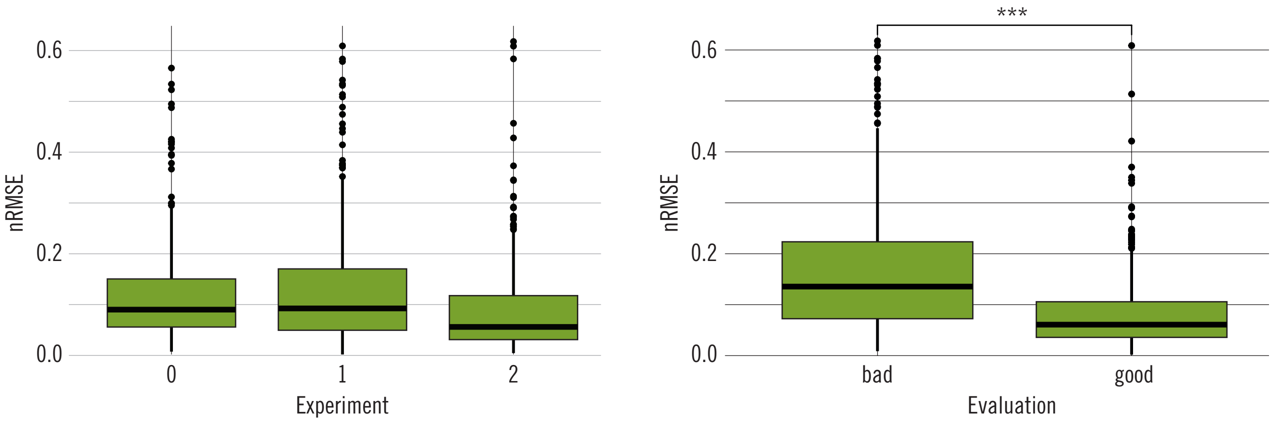

Figure 5 • Left: nRMSE grouped per experiment. Right: nRMSE grouped according to the subjective good/bad judgment. Median values (thick black lines), 25%/75% percentiles ("hinges"), extreme values (larger/smaller than 1.5 times the inter-quartile range) from the hinge (whiskers), and outliers (single dots).

subject changed during the experiments; this was done by evaluating, at each task, Roland Fisher's cluster separateness index (Fisher 1936) for the signal clusters corresponding to the past 30 tasks (one cluster per action, resulting in six clusters). Fisher's index increases the more the clusters are separated, compact and distinct from each other; it represents therefore a measure of improvement in the "quality" of the signals produced by a subject.

« 71 » Moreover, after the experiment, we conducted a semi-structured interview with each subject, focused on

- the quality of the subject-machine learning system interaction,
- the subject's judgment of the system's learning capacity, and
- the fatigue experienced by the subject while teaching the system.

We conducted a qualitative thematic analysis on the semi-structured interview transcripts, through the conventional process of familiarisation with data, generating initial codes, searching for themes among codes, reviewing themes, defining and naming themes, and producing the final report.

Experimental results and analysis

« 72 » In a first round of evaluation, it was determined that subject #13 in Experiment 0 performed exceptionally badly (extremely high nRMSE) while subject #11 in Experiment 1 performed exceptionally well (extremely low nRMSE); data from these two subjects were removed from the analysis as they were considered outliers. To keep the data sets balanced, we also removed one subject's data at random (namely subject #7) from Experiment 2. So, the analysis was based upon data from 4 subjects per experiment.

« 73 » Furthermore, the analysis was conducted on the last 90 tasks only, in order, again, to maintain a balanced dataset, and to avoid considering the inevitable acquaintance effect that each subject went through in the beginning of each experiment (phases MB of Experiments 0 and 1 and first 30 tasks of Experiment 2).

Global statistics

« 74 » Figure 5 shows the global statistics of the experiment. The average nRMSE was 11.61% (SD = 9.23%), 12.81% (SD = 11.39%) and 8.87% (SD = 9.01%), respectively, for Experiment 0, 1 and 2 (left panel, no statistically significant difference was found using a repeated-measures one-way ANOVA test – $F(2, 9) = 3.96$, $p = 0.058$). In order to check whether nRMSE was correlated with the good/bad judgment, we also verified that the nRMSE is on average 7.9% (SD = 6.5%) and 16.76% (SD = 12.48%) in turn, if grouped according to the good/bad judgement (right panel, Welch's *t*-test yields $t(510.41) = 13.06$, $p < 10^{-4}$). Moreover, the number of good/bad judgments was 230/130 201/159 and 259/101 in turn for Experiment 0, 1 and 2, with a statistically significant difference (the Chi-squared significance test yields $\chi^2(2) = 20.15$, $p < 10^{-4}$).

« 75 » From these results we can say that

- Experiment 2 resulted in an overall slightly better error rate than Experiments 0 and 1, although the high standard deviations reduce the statistical significance of these results;
- Experiment 2 elicited more "good" judgments than Experiment 0, which in turn elicited more than Experiment 1; and
- "good" subjective judgments are positively correlated with lower nRMSE.

All in all, nRMSE values are in line with previous literature obtained from analogous experiments (Gijsberts et al. 2014; Ravindra & Castellini 2014; Connan et al. 2016).

Evolution in time

« 76 » Figures 6 and 7 go into a little more detail, showing the nRMSE and number of good/bad responses for each experiment, subject and task, along time. From these further graphs, we conclude that

- Experiments 0 and 1 produced high values of the nRMSE roughly scattered in Figure 6 all along the course of time (yellowish cells appearing all along the course of the tasks) whereas in Experiment 2 the error seems to settle to lower values in the second half;
- subjects seemed to be much happier (prevalence of "good" judgments) in Experiment 2, especially subjects #3 and #8, than in the other experiments – particularly, subject #4 almost consistently judged the performance as "bad."

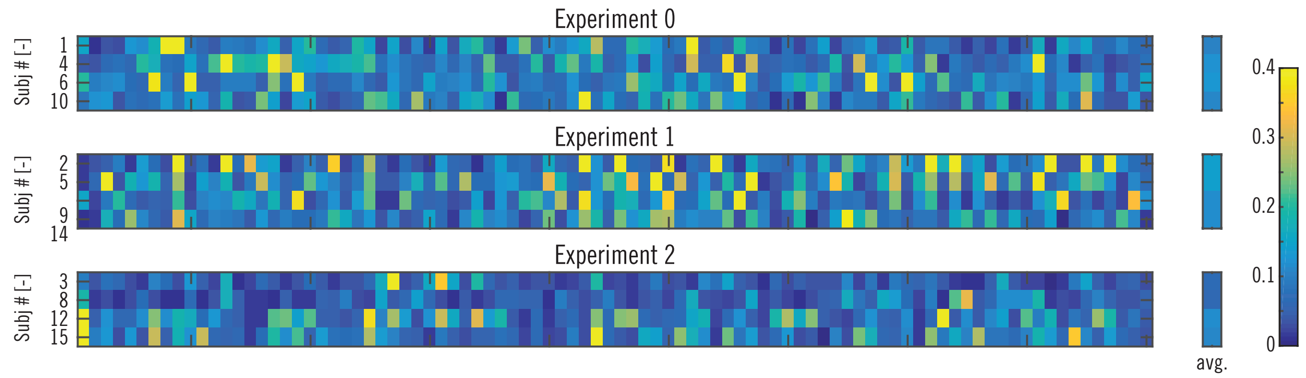

Figure 6 • nRMSE for each experiment, subject and task, as the experiments progressed.

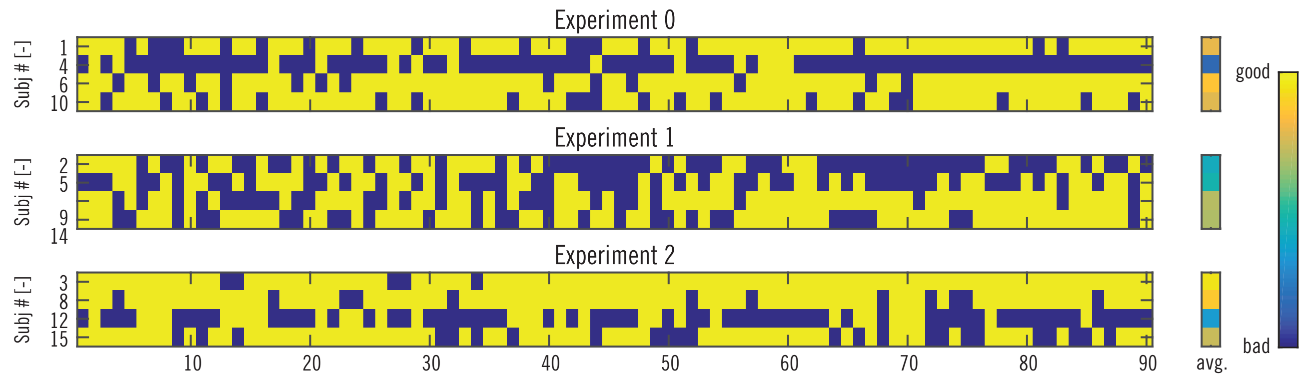

Figure 7 • "Good" (yellow) and "bad" (blue) judgments for each experiment, subject and task, as the experiments progressed.

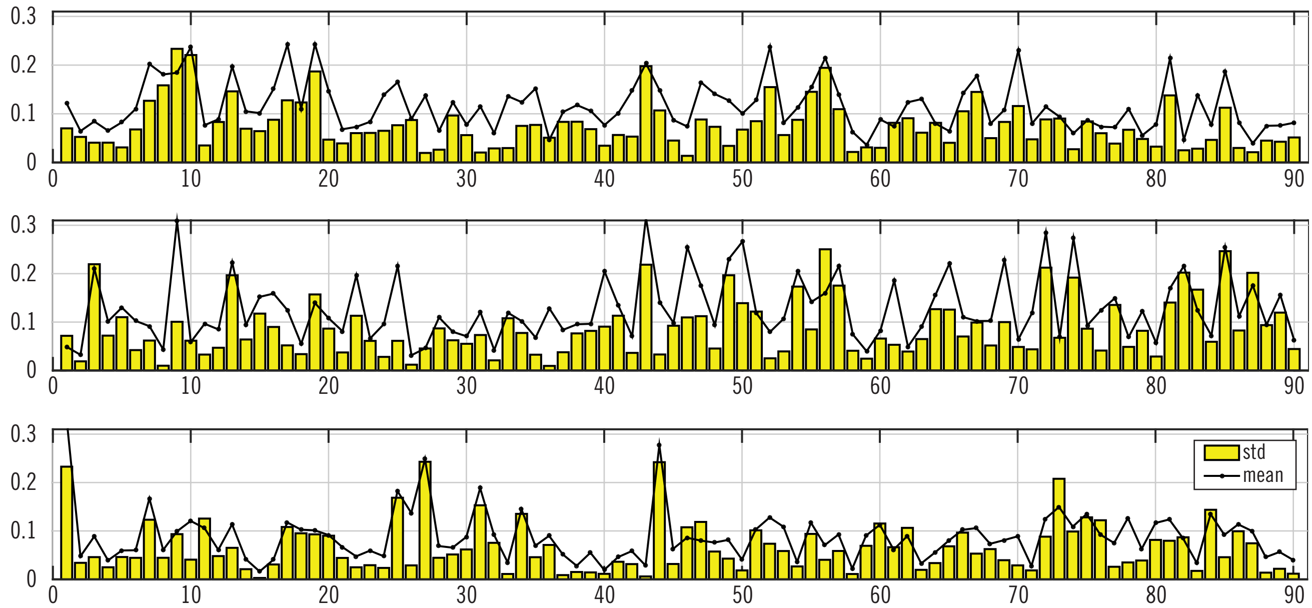

Figure 8 • Mean nRMSE and its standard deviation, averaged across subjects, for each experiment. Top to bottom: Experiment 0, 1 and 2.

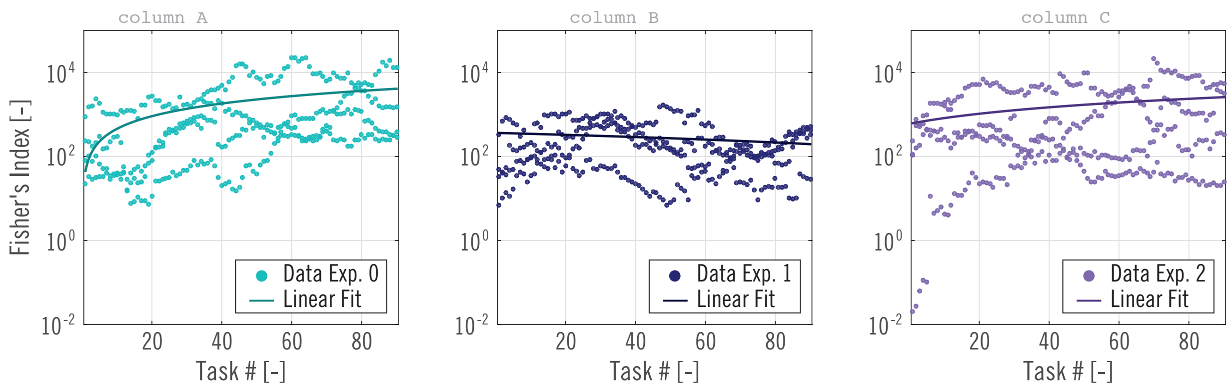

Figure 9 • Fisher's separateness index for each experiment (Experiment 0, 1 and 2 from left to right), plus linear interpolants (since the y-axis is logarithmic, they appear as logarithmic curves).

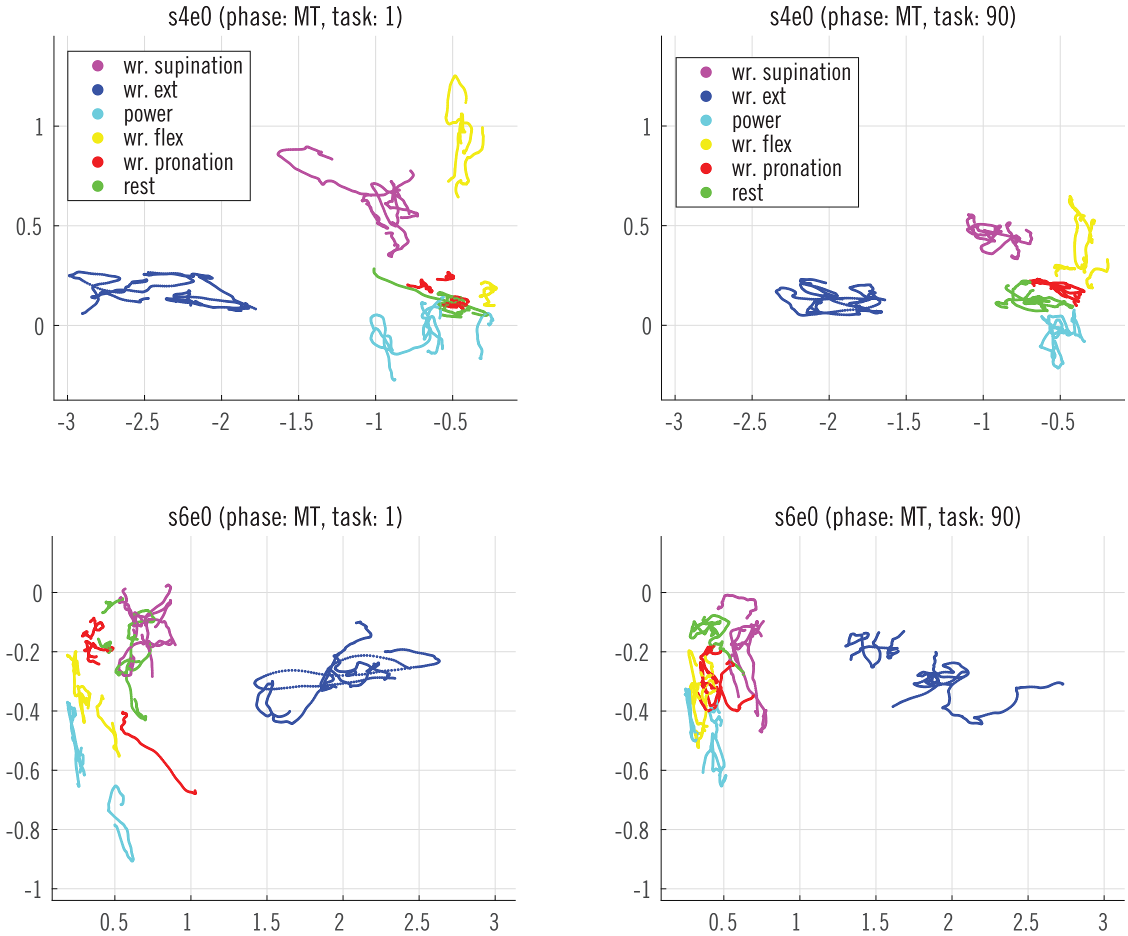

Figure 10 • Change in the signal clusters as two subjects (#4, upper panels and #6, lower panels) progress from task 1 (left column) to task 90 (right column) of Experiment 0. Dimensionality reduction obtained using Principal Component Analysis; the first two principal components retain 90.73% of the signal variance for subject #4 and 95.40% for subject #6. See also "Additional material."

« 77 » Figure 8 shows the temporal evolution of the nRMSE, averaged across all subjects (mean values and standard deviations), which confirms (consider §76 again) that not only the mean values, but also the standard deviations of the nRMSE remain lower in Experiment 2 than in the other two Experiments.

« 78 » Figure 9 shows Fisher's index along time, for all tasks, subjects and experiments. Experiments 0 and 2 elicited, on average, an increase in the separateness of the signal clusters.

« 79 » Lastly, Figure 10 shows 2D-reduced signal clusters obtained from two subjects, #4 and #6, at tasks 1 and 90 of MT in Experiment 0. (These two subjects are chosen as an exemplary good and an exemplary bad subject.) The higher compactness and separateness of the clusters at task 90 (that is, at the end of the Experiment) is apparent, especially for Subject #4. Subject #6 shows poorer cluster separateness, though – five actions appear "lumped" together.

Semi-structured interviews

« 80 » The semi-structured interviews we conducted allow us to conclude, in the first place, that all subjects involved in Experiment 2 *complained about muscle fatigue towards the end,* whereas only one subject not involved in Experiment 2 did. This is due to the increased number of tasks performed, in turn due to the possibility of judging "bad" and potentially having to repeat the previous action at all times. The finding that the nRMSE obtained in Experiment 2 seems not to particularly increase towards the end (Figure 6 and 8, bottom panel), and that its standard deviation remains low (Figure 8, bottom panel), is all the more remarkable.

« 81 » Secondly, no pattern is apparent in the judgments along time (Figure 7); we found that, each subject approached the Experiments with seemingly different hopes and expectations. For example, subjects #4 and #12 mostly judged "bad" and both reported posture/muscle discomfort; subjects #2 and #5 judged "bad" quite often, the former reporting difficulty in rating the movements only as good or bad and the latter reporting frustration due to the "continual oscillation" of the prosthesis; lastly, subjects #3, #6 and #8 mostly judged "good," and all reported being "positively impressed" by the progress obtained by the prosthesis in the beginning.

« 82 » It is interesting to note that, upon a closer look at Fisher's index for each subject (not displayed), subjects who mostly judged "good" consistently ended up with higher Fisher's index and vice versa.

General remarks

« 83 » The experimental results shown above let us make a few claims. Given the low number of subjects involved, matching the semi-structured interviews with the experimental results allowed us to add a "layer" of meaning-for-the-subject of what happened during the experiment, offering us clues on how to read the data gathered in the experimental setting. Something particularly useful in a pilot study with a small number of subjects, but also useful in general in experiments involving human beings.

« 84 » The subjective measure of satisfaction, that is the good/bad judgments, is by and large in agreement with the objective one for the experimenter (the nRMSE), as is apparent from Figure 5, right panel: on average, whenever the subjects saw that the prosthesis was "doing the right thing," they judged "good" and vice versa. This shows that the voice and visual interaction was well designed. As opposed to that, the experiment number (0, 1 or 2) turns out to significantly skew the number of good/bad judgments (for instance, Experiment 2 elicited significantly more "good" than "bad" judgments) but *not* the nRMSE: although the error is on average lower for Experiment 2 than for 0 and 1, and lower for 0 than for 1, it is not significantly so. These two remarks seem to somehow collide, but it is not yet clear to us in what sense.

« 85 » There is a significant evolution in time of the subjects' signals (Figures 9 and 10 – consider the attached video clips, too) during Experiments 0 and 2. We speculate that the increase in Fisher's index during Experiment 2 could be due to the concurrent evolution of the subjects and the machines. Notice, however, that during Experiment 0 the ML model was not adapting at all during the MT phase, although some of the subjects involved in Experiment 0 reported that they felt that "the machine was learning."

« 86 » All in all, the "partially interactive" experiment, that is Experiment 1, seemed to produce slightly worse results than the non-interactive one; whereas the "fully interactive" one, Experiment 2, produced slightly better objective results than both the other experiments, and definitely better subjective results – higher satisfaction expressed by the subject.

« 87 » Muscle fatigue seems to have played a significant role in the experiment, which we had not foreseen. Unfortunately, this was mostly the case in Experiment 2 since interaction means more tasks to perform by the subject. Still, the error in Experiment 2 is more "uniform" (lower mean, lower standard deviation) than in the other cases. A further refinement of the experimental design will need to take into account fatigue as an unavoidable problem; but we should at the same time remember that fatigue is one of the factors that make myocontrol a non-stationary modelling problem, that is to say, one of the problems that iML should be better at tackling, in principle.

Conclusion

« 88 » One must admit that, if taken from the point of view of the engineer, the results of the experimental analysis are somewhat disappointing – there is no definite, statistically significant objective improvement (although there is some) when enforcing more interactivity, also conceptualised in line with RC's learning theory. Still, the subjects involved in the experiments generally reported a smoother interaction with the ML system in the case of Experiment 2.

« 89 » Therefore, the missing suggestion that the RC approach gives to the ML practitioner – that of using RC-framed iML – goes farther toward creating a better experience for the user of an upper-limb prosthesis. The application of RC to this problem gives us useful insight into how to design the interactive prosthesis of the future; points us toward more ecological experiments, more deeply embedded in daily life, aiming at enforcing interactivity with the subject at all times, just like it happens with modern gadgets such as, e.g., smartphones. Reciprocal adaptation inspired by RC's learning theory seems to definitely be a factor to be exploited in this field.

« 90 » The main contribution of this work is to reframe iML within radical con-

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structivism. Although still far from fully tackling the theoretical implications of this idea, in this article we try to show what the potentialities of such a link are. Especially, we expect the marriage between RC and ML to produce, in the near future, a set of guidelines on how to design the ML "statistical engine" and the interaction that is at the core of interactive machine learning: how to reframe interaction and feedback according to RC's learning theory. What should be asked of the human operator, how and when? How should the information so obtained be used? Neither the engineers' community, nor the world of functional assessment can, at this stage, thoroughly answer this question.

« 91 » Extensions to this research should definitely include at least the capability, for an RC-framed ML system, to decide *internally, autonomously* whether a signal is not a good one. This means that the system must trigger *by itself* a perturbation whenever a signal does not fit its conceptualization (model) of the world, thus enforcing the RC idea of *viability* related to *conceptual coherence.*

« 92 » All in all, this article has explored the application of radically constructivist "glasses" to a typical problem in human-robot interaction, and specifically to upper-limb myocontrol. More generally, we have tried to rework, in RC terms, some of the problems faced by ML and iML; we have speculated that the usage of RC-framed iML matches some of the ideas that, among others, von Glasersfeld applied to human learning. Our results suggest that RC-inspired interactivity has the potential to improve human-robot interaction, especially from the point of view of the humans.

Additional material

The dynamic 3D evolution of the clusters from Task 1 to 90 can be seen in two short movie clips at http://constructivist.info/data/13/2/s4e0.gif and http://constructivist.info/data/13/2/s6e0.gif.

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Open Peer Commentaries

on Markus Nowak et al.'s "Applying Radical Constructivism to Machine Learning"

A Radical Constructivist Approach to the Human-Machine Interface

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> Upshot • Thousands of projects aimed at improving the functionality of upper-limb prostheses over the decades have failed to significantly advance the field of assistive robotics. Having been unfamiliar with radical constructivism (RC) so far, I want to see how its approach could contribute, particularly for amputees. Perhaps the most profound insight to be gained from RC is that the prosthesis is the machine to be taught by the user to serve her needs, not the other way around.

« 1 » Current myoelectric (hereafter "myoe") control systems for upper-limb prostheses embody a small repertoire of utilitarian movements that can be executed individually upon user activation of specific muscles in the residual limb. The movement repertoire is severely limited by inadequacy of the user's interface with her prosthesis, i.e., the human–machine interface (HMI). Thus, while the mechanical hardware of modern robotic hands can nearly or completely reproduce human dexterity, prosthetic users cannot, and new control paradigms are urgently needed. Currently available HMI's are non-intuitive, and demand much more mental attention than do natural movements. Typically, prosthetic grasping is triggered by user volition for "wrist flexion" (despite the user's having no functional wrist), that produces a particular muscle activation signal in the residuum. In some prostheses, several different similarly pre-programmed tasks may be activated, depending on the user's ability to learn and produce a sequence of the correct muscle activations in her residuum. The practical utility of a prosthesis thus depends on the user's ability to learn not only the right moves by her residuum, but also of her body poses, which are an important part of the motor control loop (Metzger et al. 2012). Functionality also depends upon the situation: relatively good control can be achieved under relatively fixed, static conditions; however, in situations requiring careful calibration of overall body movements (e.g., carrying an egg), it falls short. In general, most activities of daily living that involve manipulation, and certainly any tasks that require dexterity, exceed the capabilities of available HMIs. A common failure that cannot be fixed by the myoe controller is malfunction of the sensors themselves, commonly caused by sweating or dislodgement, which is not the fault of the ML. Alternative sensors of muscle activity, which are less subject to failure, have been demonstrated (Castellini et al. 2014: 22), but are not yet widely adopted. Thus, for several reasons, including some that have nothing to do with the type of ML used, many users of upper-limb prostheses abandon theirs.

« 2 » Myoe controllers, in their most primitive (typical) configuration, direct pre-programmed prosthetic actions upon receiving signals from specific muscles. Muscular activities are statistical events that can be compared against an explicitly pre-programmed value, a paradigm that is considered to be a form of machine learning (ML) (§2). Any muscle signal that exceeds a pre-set amplitude threshold produces a binary "1" input to the prosthesis. In some cases, the user can serially trigger several different prosthetic motions from a pre-programmed repertoire, by executing particular sequences of discrete motions, each of which produces distinguishable muscle contractions. The potential movement repertoire is limited by the skill and patience of the user in producing strings of supra-threshold muscle contractions, and the abilities of the HMI (computer) to compare the input with the pre-programmed threshold. One advantage of the current myoe paradigm is binarization of muscle activations, which provides relatively noise-free, unambiguous examples to serve as ML inputs; this feature, however, is at the expense of information about movement magnitude and force.

« 3 » RC theory requires any "viable" model of the world to be both utilitarian and "conceptually coherent" (Glasersfeld 2005), so we can ask whether the realist model is viable (§17) and otherwise conformable to RC principles. In terms of RC, the realist model embodies *utility*, i.e., it produces at least one useful task fairly well: grasping. With regard to being *conceptually coherent* (§17), however, it fails, since there are now better solutions to the problem. Moreover, the RC idea of "learning as a constructive activity" requires *continual* learning by the prosthesis as it interacts with its user, representing a 180-degree shift from the current myoe control paradigm. The current myoe model, as described in the first two paragraphs above, is based on a "'realist" attitude, which assumes, according to §11, continual performance as programmed, requiring “no further changes.” If accurate, this attitude would represent the antithesis of RC principles, however, it may be a bit exaggerated if taken too literally. The need for periodic myoe program adjustments is widely recognized and in practice, and changes are implemented where practical, regardless of what type of controller. In the traditional sense of the word, “viable,” however, we must acknowledge the practical viability of realist myoe control, because it serves many thousands of amputees.

« 4 » The RC framework, as elaborated by Markus Nowak, Claudio Castellini and Carlo Massironi, introduces a radically new, and possibly improved, prosthetic control paradigm. The first and most obvious insight from RC is that our present prosthetic model employs a strategy opposite to machine learning: instead of the prosthesis learning the proper responses to the user, *it* acts as the teacher, demanding the correct input from the user (who is the learner) for proper performance. A second insight is the potential pitfalls of a supposed *realist* attitude to statistics. Muscle activation signals are composed of Gaussian noise, generated by a large number of asynchronous motor units, which are variably active for each movement in a sequence. The application of a statistical test to such signals, using fixed decision boundaries, is bound to lead to erroneous decisions, since two identical events, such as sequential movement commands, can be statistically different in their muscular representations. Thirdly, the idea of incrementally updating the controller (incremental ML) is integral to constructivism. This process, iML, was demonstrated in the pilot studies, consisting of constant monitoring and teaching of the prosthesis by the user (§65), and appears to be viable.

« 5 » It is useful to compare the current (realist) myoe model with a hypothetical RC-framed control model. Current myoe systems treat their input as an unequivocal signal, either to be detected or rejected, according to its magnitude. RC insight recognizes that inputs to an ML system exist only as “perceptual objects” that must by organized, without knowledge of their meaning. This is an important reminder that ML inputs represent a “reality” constructed by myoe sensors and thus constitute a noisy estimate of reality, which in our case consists of muscle activations. These perceptual objects must be matched against patterns consisting of objects perceived by an imperfect system. This framework compensates for mistakes and mis-interpretations, by incorporating explicit procedures for correcting them. This ongoing positive feedback tends to promote positive emotions between user and her assistive robot.

« 6 » It is also useful to evaluate the pilot study of incorporating RC principles into prosthetic control (§38 ff). The experiments were elegantly designed and executed, but the results rather disappointing (§88). Here, I critique the experimental design from my interpretation of RC principles.

« 7 » Firstly, training the prosthesis (machine) was done by subjects performing general movements and static positioning of joints related to their hands. While the prosthesis may more easily execute these movements, they do not fit well within the RC framework. The protocol involved no purpose, and lacked motivation. Humans like to perform *tasks*, especially those that are interesting, challenging, and have *utility* (Gorsic et al. 2017). Examples of this phenomenon can be seen in previous studies wherein motor-disabled persons and amputees taught their virtual prosthesis to play and win standard games, such as pegboard (Kuttuva et al. 2005; Yungher & Craelius 2012).

« 8 » A second critique is testing *non-disabled* subjects on the use of an assistive robot. From an RC perspective, this seems *conceptually incoherent*. Persons with motor disabilities may be better teachers of assistive robots than able-bodied persons, as suggested by the two studies cited above. In a study of 12 persons with arm paresis due to brain injury playing a virtual pegboard game wearing a sensor sleeve on the affected arm, a significant improvement in speed of 15% was achieved after 30 trials with their virtual assistive robot; controls, in contrast, showed negligible improvement with their prosthesis (Yungher & Craelius 2012). Qualitatively similar results were found in a smaller study comparing virtual prosthetic teaching by controls with that of persons having upper-limb amputation (Kuttuva et al. 2005). A final critique relates to the anatomical differences between the residuum and the intact limb. Muscles and tendons in the residuum are radically rearranged, and any natural synergies among them are disrupted. Additionally, the typical conical shape of the residuum may be a better substrate for sensor sleeves, which can readily accommodate 32 sensors as opposed to 8 sensors typically applied to sound limbs.

« 9 » Since the experiment with subjects (§55) incorporated their vocal feedback to the prosthesis via speech recognition (SR), it is interesting to compare that technology, perhaps the oldest and most common ML system, with the current myoe ML system. There are four ways in which the systems differ radically from each other:

- myoe systems are necessarily custom-tailored to individual users, whereas SR systems are designed to be universal,
- myoe systems are trained with relatively few examples, whereas SR systems are trained by as many examples as possible,
- SR is inherently interactive, whereas current myoe systems are not, and
- SR employs statistical *predictive* methods, unlike myoe, which does this minimally.

« 10 » At the same time, myoe and SR systems share a major commonality, since both can be considered *recursive translators*. An SR translator interacts with a human who verbalizes an idea as words in one language, interprets those and translates the idea into words in another language. The myoe controller interacts with a human who expresses a desired movement by muscle activations, and interprets those and translates the desired movement as a robotic movement. It is noteworthy that speech recognition was not too long ago ridiculed as “crack-pot” by some, whose anecdote referred to the case when a computer program translated the phrase, “out of mind, out of sight” into Chinese and back to English, and it replied, “blind idiot.” We see analogous sorts of anomalies occurring in myoe control, when the prosthesis “goes off the rails,” but given progress along the right directions, as exemplified in this pilot study, assistive robotics technology may now be at a developmental stage resembling that of SR several years ago. When prosthetic controllers achieve the same accuracy as speech recognizers, amputees will then be able to enjoy a high degree of dexterity.

William Craelius received his PhD in Biomedical Engineering from Northwestern University, and did Postdoctoral training in Neuroscience at Stanford University. In 1999 his team at Rutgers University developed *Dextra*, the first "multi-finger" controlled prosthesis, which was used by an amputee to play a short piano piece, broadcasted on the BBC. He currently is Professor of Biomedical Engineering at Rutgers University, where he founded the first MS Degree Program in Prosthetics. He is a Distinguished Fellow of the *National Institute for Disability Research and Resources*, and Fellow of the *American Institute of Medical and Biological Engineers*. Webpage: http: //www.dextrahand.org

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The EMG Properties Limit Ultimate Classification Accuracy in Machine Learning for Prosthesis Control

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> Upshot • Machine learning (ML) has been applied in many forms and under many names over the years to the problem of mapping arrays of surface electromyogram (EMG) signals measured on the arm of a person with an amputation and then trying to correlate those signals to the control of multi-degree-of-freedom prosthetic arms. While being intrigued by the idea of the interactive machine learning (iML) component of the study, I am not surprised that iML did not do noticeably better than standard approaches. The issue, as demonstrated by many researchers, is not our ability to do ML but rather the fundamental problem associated with using EMG as the inputs to the ML system and the clinical issues associated with stable acquisition of those signals.

« 1 » Markus Nowak, Claudio Castellini and Carlo Massironi present a flawed argument for the problems of machine learning (ML) in EMG control of multifunctional upper-extremity (UE) prostheses. Also, they present an engineering-/science-centric view of persons with amputations and how they use their prostheses as justification for the use of advanced ML techniques, with little understanding of the *clinical* drivers for the current state of UE prostheses control.

« 2 » In §10 the authors claim that

> "machine learning tends to be used as a number-crunching black box, at which to throw as many examples as possible, hoping that it will yield a usable relationship between input data and target values. Too often, scarce attention is paid to the quality, the origin and the meaning of the examples […]"

I claim that the authors and others are guilty of exactly this. If we stopped to consider the problem a little more, we might be able to achieve a different result.

« 3 » First, we need to consider the population for whom we hope to fabricate hands and arms. Persons with trans-radial (TR) level amputations make up more than 70% of the upper-limb amputee population. For 99% of these individuals this is a unilateral involvement. Of this TR population 80% will use some sort of prostheses. But the implication of the unilateral involvement is that most people with an upper-limb amputation still have a good limb that they will use, over their prosthesis, for most tasks. This makes the barrier to acceptance for UE prostheses very high and means that anything that is perceived as heavy, uncomfortable, bothersome, or a hassle will not be used.

« 4 » Trans-humeral (TH) level abandonment rates tend to be higher because of the need for an elbow, which serves to isolate the hand from the residual limb. Here abandonment rates are at about 50%. This population makes up 10–15% of the UE population. So, when Nowak et al. say in their abstract that "[d]espite more than 40 years of academic research, myocontrol is still unsolved, with rejection rates of up to 75%," this appears to be a hyperbole used to justify their technology. I consider it not accurate as it continues to propagate the myth that the current devices are not useful.

« 5 » Second, we need to consider standard-of-care fitting practices and why we are where we are. The most common standard-of-care myoelectric (EMG control) fitting is a 2-site myoelectric prosthesis for persons with TR loss. Myoelectric systems have been widely accepted as a viable clinical option since the 1980s and in particular the TR myoelectric fitting has found success due to its cosmetic appeal, lack of suspension straps and high grip strength, but system robustness, weight, and cost are still issues (Atkins, Heard & Donovan 1996). A standard 2-site myoelectric system is typically limited to 2 degrees of freedom (DoF) with a co-contraction, or rate, used to switch between DoF because, in general, one can only get 2–3 independent *surface* EMG sites on the residual limb of a trans-radial subject before cross-talk becomes an issue (Ajiboye & Weir 2005). It is the limited number of control sites and the associated limit on the number of controllable DoF that led investigators to explore other means of acquiring and using multi-DoF control schemes such as ML. Users certainly want more DoFs, but not if it is a hassle.

« 6 » Pattern recognition (PR, which is what the field of prosthetics control calls ML) was first explored in the 1960s (Herberts et al. 1973; Lawrence & Kadefors 1974; Taylor & Finley 1974) and reinvented in its current form in 1993 (Hudgins, Parker & Scott 1993). Since then it has undergone much development (Englehart & Hudgins 2003; Scheme & Englehart 2011; Sensinger, Lock & Kuiken 2009; Farrell & Weir 2008a, 2008b; Simon, Lock & Stubblefield 2012; Zhou et al. 2007) to get it to a point where it could transition to the clinic. PR algorithms seek to correlate *patterns* of EMG activity with a *given/desired* arm motion or hand posture. EMG signals are measured by an array of myoelectrodes on the residual limb. Other "features" in addition to amplitude are extracted and correlation between the EMG activity pattern and a desired motion is determined by *training* an ML algorithm/classifier with the extracted features for each EMG signal.

« 7 » Currently, a good ML/PR classifier can readily achieve about 90–95% accuracy. During training, patterns of muscle activity are recorded while the user holds a desired posture. Multiple trials are recorded for each posture. This has to be repeated for every desired posture. One can see how, if a large number of different postures are desired with multiple trials for each posture, training the system can get tiresome for the user quickly. Also, as currently implemented, PR is sequential in nature and users are limited to only those postures that they have trained the ML system to recognize. So far, because of this, PR techniques have met with little success outside the laboratory, so why is this so?

« 8 » Returning to the idea that the barrier to success is high for persons with unilateral amputations – the training is a bother that has limited pattern recognition adoption. People want to put on their prosthesis and go. They do not want extended training periods every time they don their arm and they do not want to then have to repeat the training throughout the day as the environment in their socket changes the electrode properties. As a result, it has taken a long time for PR systems to make it to the clinic.

« 9 » Third, we need to consider the nature of the EMG signal used for the control. The raw myoelectric (EMG) signal is a broadly Gaussian random signal whose amplitude increases with muscle contraction level. This signal needs amplification/filtering/integrating/processing to extract the RMS value for use in amplitude-based myoelectric control (Childress & Weir 2004; Parker & Scott 1985). Filtering adds a delay to the system, decreasing system responsiveness, which, if excessive, frustrates the user. Furthermore, EMG control provides no feedback – myoelectric signals are recorded on the surface of the skin and sent out to the motor and nothing deliberate comes back. Incidental feedback in the form of motor whine and socket pressures are used by skilled users. Clinical issues such as motion artifact, skin impedance changes and electrode lift-off also present challenges that must be overcome during the fitting process.

« 10 » When using EMG signals as inputs to the ML algorithms, the random noisy nature of the EMG signals presents difficulties for ML classifiers of choice. Small changes in electrode position can have a dramatic effect on the machine-learning/classification accuracy. Donning and doffing the prosthesis can alter the classification. As the number of degrees of freedom (DoF) to be controlled increases, moving from one posture to another may result in overlapping muscle activity patterns, reducing the ability of the classifier to separate the EMG patterns. In addition, extrinsic factors such as electrode movement, electrode lift-off, changes in skin impedance, or moving to positions outside of the initially trained position or using the prostheses under varying loads or in different positions can all significantly degrade classifier performance (Fougner et al. 2011). This makes it extremely difficult for PR systems to find success with users.

« 11 » Finally, we must understand that the goal of research into ML systems for UL prosthesis control is to build systems that will someday be worn by individuals with limb loss and that given what I said above in §§3f there are a host of clinical issues that will be ultimate drivers of success.

« 12 » The way CoApt, LLC, (Chicago, IL) was able to circumvent these issues and launch the first clinically successful pattern-recognition system was to use an eight-electrode system to control 1 DoF in the hand (no grip patterns) and only 3 DoF in total (hand, wrist, and elbow) (Uellendahl & Tyler 2016; Baschuk et al. 2016). This enables a user to do the "on-the-fly" training using CoApt's prosthesis guided training (Lock et al. 2011; Simon et al. 2011) system, which since users are only controlling 2–3 DoF, does not have onerously long training. In a field that has been locked into only 2 electrodes as standard of care, CoApt's approach of providing a system of 8 integrated myoelectrodes to control 2 DoF is changing how clinicians and researchers are thinking about the provision of myoelectric care.

« 13 » What we see is that it was a knowledge of the field and the population to be fitted, as well as a clinically viable way to allow training by users on the go that enabled the CoApt system to move from the laboratory to the field. The ML algorithm CoApt uses is not sophisticated, just good enough, because it is not the determinant for success. What we see in ML/PR is that by using every available technique (including fuzzy logic, linear discriminant analysis (LDA), principal component analysis, non-negative matrix factorization, self-organizing feature maps, support vector machines, random forests, cepstral constants, neural networks, and multinomial regression) a classification accuracy of about 90–95% can be achieved but not more. So, in the field of prosthetics control, the LDA classifier with a time-domain feature set or auto-regressive constants has become the standard, because it is low cost from a computational perspective, easy to implement, and is as good as anything else. Could the authors expand on the feature set as well as the actual classifier they used? There was a lack of detail on the actual classifier used and no mention of the features used to train the classifier.

« 14 » So, bottom line, the interactive aspect of the iML trial is an interesting concept in the target article, and ought to be a good thing in the long run. Talking to the subject and telling them as the training session progresses that a training movement is "good" or "bad" and then only using the "good" training datasets to build the classifier ought to bias the classifier training dataset to "good" examples. But when I read that ultimately the iML pilot study results did not show much improvement it did not surprise me. It is hard to get beyond the 90–95% classification accuracy rate, since this is most likely a consequence of the poor properties of the EMG signals used as the system inputs. We need to do something different with the EMG signals or integrate them with other types of input signals.

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Choosing the Right Observables

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> Upshot • The stripped-down experimental setup may be missing important sensory proprioceptive and tactile observables that may well be crucial for designing useful, effective, and flexible general-purpose motor prosthetic devices. Because trainable machines cannot by themselves add new observables, designers must foresee which ones are needed.

« 1 » Motor substitution – the replacement of organic effector organs with artificial ones – has long been stymied by the problem of control – how to effectively control the artificial muscles using neural and/or muscle signals that are produced by the human operator. Markus Nowak, Claudio Castellini and Carlo Massironi address the problem of controlling arms and hands via muscle activation signals (myocontrol) observed via electrical sensors (upper arm electromyography (EMG)).

« 2 » Their target article focuses on the human-machine feedback loops in play when one has a human training and operating an adaptive prosthetic device. After first introducing machine-learning schemes, the discussion quickly moves away from the ultimate problem of effective motor substitution and into the stripped-down experimental setup, where an adaptive machine controller is trained to produce a small set of six alternative discrete static wrist-hand positions (§51: rest/no-action, wrist supination, extension, flexion, pronation, and hand-closing). The adaptive controller decides how to move a simulated hand given a particular goal (a target wrist-position category) and the eight-channel EMG output of the *Myo* bracelet (§42), which here is worn by normal subjects with intact upper limbs. The main focus of the target article is on the role of human-machine interactions during different stagings of model building and training phases.

« 3 » Effectively solving the problem of motor substitution will substantially enhance the lives of many people, and I think the limited experiments outlined here are well worth pursuing. Innovations in design strategies and how we think about them also have large ripple effects in other domains, such that bringing constructivist ideas to the design process have implications far beyond prosthetic devices (as I say, *all technology is prosthesis*, in that every technology that is meaningful is some amplification or augmentation of our biological, bodily and mental functionalities).

Motor control under natural vs. experimental conditions

« 4 » In order to understand the experimental setup, I found it necessary to draw schematics that depict the functional organizations of humans with intact upper limbs vs. those of the trainable machines that are considered here (Figure 1). The first order of business when evaluating a system that is designed to operate in non-virtual realms is to examine its goals (the functions it implements, whether for itself or in service of a designer's goals), what its observables (measurements, realized through sensors) and modes of action (realized through effectors) are, and how these are coordinated (how percept-action mappings are determined). These are the basic functionalities of any *purposive, percept-coordination-action system* (Cariani 1989, 2011, 2015). A system is *purposive* by virtue of embedded goals, evaluation mechanisms for assessing whether goals are attained (satisficed) or better performed, and means of directing or steering behavior to better attain goals. For each goal, the steering mechanism consists of a percept-action mapping, i.e., how the system should behave given its sensory inputs (its-current-observed-state-of-its-environment) given that current goal. Such a system has *agency* vis-à-vis that goal if it has the autonomy to pursue attainment of that goal.

« 5 » In the target article, we have two adaptive, purposive percept-coordination-action systems that interact to train each other, namely the human operator and the trainable prosthetic device. This could be seen as two problems of first-order cybernetics: how does the human best give evaluative feedback that trains the machine to recognize different muscle activation patterns (EMG signals), and how does the machine train the human to modify patterns of muscle activations such that it can better classify the signals? Provided that the two systems have enough variety in their responses and in channels that mediate their communications for mutual adaptation to be possible and functionally beneficial, we can also view this as one problem of second-order cybernetics in which the dynamics of the interactions might be crucial.

« 6 » However, whether the order of interactions ultimately matters in improving the quality of prosthetic movements may depend on whether there is room for improvement. If the human user cannot effectively learn to change muscle activation patterns that are observable via the eight channels of EMG or the trainable machine is already exploiting the limited data it has to the fullest, then not much benefit in prosthetic function may be gained from modifying sequences of model building and testing. If I understand Figure 8 correctly, the mean hand-configuration errors (nRMSE), which quantify the similarity of the hand positions produced by trainable classifier with the target hand positions, should be improving with training. However, no such trend in the error metric is seen for any of the three experimental protocols over the course of 90 trials. This could possibly be indicative of a ceiling effect – the classifier rapidly achieves its optimal performance such that further training does not help and also that the potential benefits of modifications of the training-test protocol are hidden. As the authors note (§§80f), there are also additional subjective factors, such as perceived muscle fatigue, smoother interaction, and positive impressions of prosthesis operation that are entirely relevant to patient acceptance and use that may be amenable to improvement by adjusting training and testing protocols.

« 7 » It could be the case that including additional physiological observables would permit higher optimal levels of functioning that could benefit from mutual adaptation. Choice of observables – measurements to be made – is the most important decision to be made in constructing a predictive model, and choice of feature primitives is likewise the most important decision in designing a trainable classifier. In general, choosing

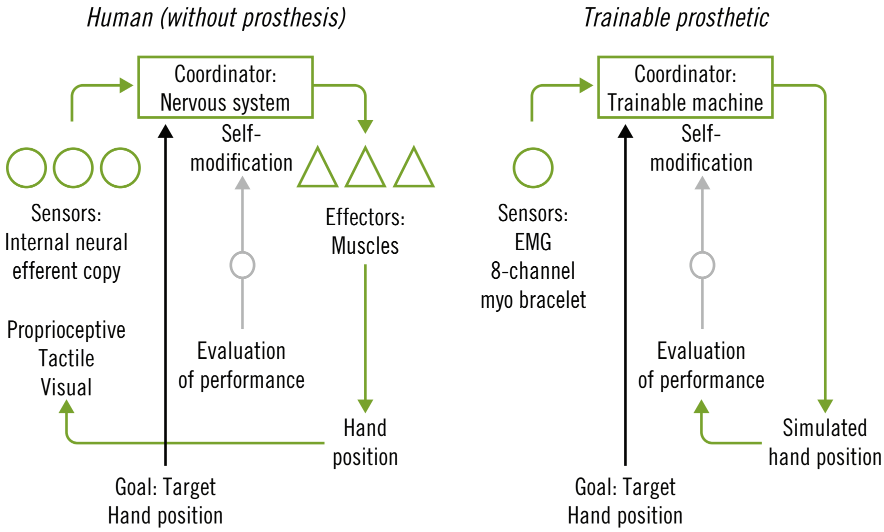

Figure 1 • Functional organization of human upper arm control (left) compared with the trainable prosthetic used in the experiments (right). Sensors that carry out measurement operations are indicated by circles, coordinations that map input sensory states to output decision states by boxes, and effectors that carry out actions by triangles. Arrows indicate causal chains of effects. Black arrow indicates goal directive (task target). Gray arrow indicates evaluative feedback about the efficacy of the last action (measurement of performance) and the operation of modifying percept-action mappings. Note that the experimental setup is highly impoverished in terms of sensory observables for feedback control and possible action states (many vs 6 hand positions).

what measurements to make, however, is an ill-defined, unformalizable, domain-specific problem for which there are no effective procedures other than building new measuring devices and trying them out. In practice, designers think of as many possible relevant observables as they can and then eliminate those feature primitives that yield no benefit. Biological systems have solved this fundamental problem by evolving new sensory receptors, modes of neural coordination, new effectors, and new possibilities for action. Long ago (Cariani 1989), I proposed a class of biologically inspired devices that would adaptively build their own hardware including their sensors, coordinative parts, and effectors such that they would construct their own primitives, thereby solving the problem, in principle at least, of finding the right ones.

« 8 » A machine-learning classifier can only be as good as its feature primitives and a machine-learning controller can only be as good as its set of possible actions. A trainable machine does not have the means of creating new feature or action primitives, such that it is prisoner to the sets of sensors and effectors its designer chooses for it. Without adequate variety in these domains, such systems can learn up to a point, but they will be ultimately constrained by the limitations of their pre-specified sets of features and actions.

« 9 » When tackling a problem in bionics, and especially when troubleshooting why artificial prostheses do not work as well as their biological counterparts, it is useful to first compare the functional organization and operational structure (physiology) of the two systems. My concerns as a physiologist, systems scientist, and cybernetician would be what the experimental setup is leaving out in terms of observables, actions, and feedbacks.

« 10 » In the normal, intact biological case (Figure 1, left), a human (or animal) has a number of sensory channels that provide critical feedback for movement and positioning of limbs. Perhaps most importantly, humans and animals have proprioceptive feedback that provides information about the limb positions and muscle stretch. I once worked on the problem of spinal cord regeneration (Wang et al. 2008), which involved facilitating the regrowth of neural connections between proprioceptive afferents and their associated sensory pathways in the spinal cord. Despite intact muscles and motor neurons, rats deprived of neural signals in forelimb afferents completely lose the use of their forelimbs, but once these connections are restored, functions also return. Humans who have lost their proprioceptive afferents through disease have great difficulty executing movements such as walking, and only through concerted, sustained attentional effort can they learn to use visual feedback to guide their limbs. In many common situations, we can also benefit from tactile feedback. There are also thought to be neural efferent copy signals that provide the brain with copies of the command signals that are activating muscles. As far as I can tell, the present prosthetic setup involves only eight channels of EMG data that would be analogous to using motor command signals or their efferent copies. There is thus visual feedback, which may be adequate for simple, static hand positions, but there is no proprioceptive or tactile feedback, which might be necessary for flexible movements or grasps. If I were involved in the problem of designing a flexible, general-purpose prosthetic device, I would look first to incorporating proprioceptive and tactile feedback signals from artificial hands and arms into prosthetic controllers (Ciancio et al. 2016). Incorporating whole new classes of observables is, of course, a much more formidable task for an experimenter, so it is entirely understandable why the experimental setup reported here would not (yet) include them.

Understanding the experiments

« 11 » The experimental setup in the target article is complicated to the uninitiated and is confusing to sort out, especially if one is more focused on the motor substitution problem than on human-machine interactions. The nature, adequacy, robustness, and informational content of the eight channels of EMG data and the effects of alternative machine-learning algorithms are never spelled out in detail: Are they operating on time-series EMG data? How similar are signals from amputees and non-amputees? How many independent dimensions or distinctions can they convey? Does performance using the *Myo* bracelet data depend critically on the type of machine-learning algorithm that is used? However, these considerations may be critical for interpreting these results and for solving the more general problem of designing prosthetic devices that are going to be practically useful to their users. There are many detailed technical questions that can be asked concerning the transferability of findings from the experimental setup to the practical situations of amputees who will use such devices.

« 12 » The multiple means of evaluation and sequencing of performance and training trials further complicate understanding. Multiple means of evaluative feedback included human subjects seeing their own hands or seeing simulated hands on a computer screen and giving good/bad judgements vs. machine-based distance geometry metrics (nRMSE) of hand configuration similarity. However, was the nRMSE metric used directly in some cases to train the machine or was the training feedback always from the human operator (good/bad) and the nRMSE simply used as a non-subjective (intersubjectively verifiable) measure of the accuracy of the system? (Q1)

« 13 » In §22 *interactive machine learning* (iML) is contrasted with good-old-fashioned *machine learning* (ML) in that a human operator, rather than some completely artificial evaluation process, provides physiological observables (eight channels of upper arm EMG) and feedback to the trainable classifier/controller (as seen in Figure 2 of the target article). In this case, it seems that by far the most important role for the humans in this setup is to provide the EMG patterns (via the *Myo* bracelet cuff on the operator's right arm) that will be classified by the trainable machine to generate simulated hand positions. In this situation we have two adaptive systems, the operator, who may be learning to adjust muscle actions in order to steer the trainable machine to produce more appropriate hand positions, and the trainable machine, which is simultaneously updating its classification of the EMG data based on the evaluative feedback it receives from the user. Given that the evaluations of six simulated hand positions by human trainers are binary decisions (good/bad) concerning the similarity of target and produced (the 3D simulated and visually rendered and displayed images in the figure) hand positions, could the evaluative feedback have been easily replaced by the nRMSE distance-geometry metric? (Q2)

« 14 » On the other hand, perhaps the main rationale for making the human operator give explicit feedback is to focus the operator's attention on the task and to provide greater reward when desired actions are obtained. From the increasing separations of the EMG patterns depicted in Figure 9, the training of the human operator did appear to significantly modify the EMG signals that are picked up from the Myo bracelet. One would think that this greater separation of input signals would cause the system to make fewer confusions that produce classification errors. However, as the authors remark (§88), the effects of training on performance appear to be minimal. The time course of the position-error metric (mean nRMSE) in Figure 8 shows no obvious improvement with training (trial 1 to trial 90). The hand-position separations at the first and last trials for best and worst performers in Figure 10 similarly show little obvious improvement.

« 15 » In summary, it appears that most of the effectiveness of the prosthetic classifier-controller is due to its ability to separate the EMG patterns without the benefit of human evaluative feedback. In these experiments, the human operator is critical in the generation of the EMG patterns but not essential for giving the trainable machine feedback. Nevertheless, I agree with the authors that interactive machine learning, which gives the user control over when and under what circumstances to update the input-output function of the machine, is nevertheless likely to be a promising strategy for prosthetic design.

Realist vs. constructivist approaches to design

« 16 » Some sections of the target article (§§34–37) discuss the effects of epistemology on design. We humans are all self-modifying, self-constructing systems, whereas most of our artificial systems are not. Machine-learning systems, to the extent that they do self-modify and self-construct, do so within much more constrained avenues of possible modifications than we humans and animals do. On the other hand, we can be clearer about what is going on within the trainable machine than we can about what is going on in the minds of its designers. I tend to prefer to talk about the capabilities and limitations of self-constructing vs. non-constructing systems rather than design paradigms, which reside in the heads of human designers, as important as these can be.

« 17 » It is possible to talk in terms of (realist) ontology-based design (§§3–12), where a physical or virtual world with a description that is meant to be complete is first postulated, and then a system within that world is specified to have some sort of effective behavior that fulfills some function. Partial, often statistical, observations of this "god's eye" universe by limited actors are then overlaid onto this postulated world. Three basic types of realism are physical realism, mathematical realism (platonic idealism), and logical realism (propositional objectivism). In realism, an objective world of one sort or another is held to exist independently of any observers, such that realists find it meaningful to talk in terms of "true" knowledge of the details of this world even apart from how one would observe them.

« 18 » An alternative to realism is to take an epistemological approach in which one adopts the perspective of a limited observer-actor. The observer-actor strives to achieve particular ends, such as predicting future events or bringing about particular desirable events), given limited means of observing the world and acting on it. The observer-actor, without needing an explicit ontology or access to any unobserved world-states, forms a (non-referentialist) model for effective prediction and action that then guides expectations and actions. This model is based entirely on tangible observations and evaluations.

« 19 » Although I have no evidence for this assertion, I would think that realist designers would be more inclined to try to design devices directly, from physical principles, whereas constructivists would be inclined towards making devices adaptive and semi-autonomous, such that they construct their own effective means for anticipation and action.

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Diving Deeply into Radical Constructivism

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> Upshot • Applying radical constructivism to machine learning is a challenge that requires us to dive very deeply into its theory of knowing and learning. We need to clarify its fundamental concepts, if possible, in operational terms. This commentary aims at outlining how this kind of clarification could look in the case of 3 such concepts: (a) the construction of experiential reality; (b) learning as a constructive activity; (c) the viability of conceptual structures.

Introduction

« 1 » One of the major experiences that led Ernst von Glasersfeld to adopt a constructivist way of thinking was his pioneering work in artificial intelligence, starting in 1959 with the machine translation project at the Centre for Cybernetics at the University of Milan, created and directed by Silvio Ceccato (Glasersfeld 1995: 7). Thus, I am rather enthusiastic about the idea of applying von Glasersfeld's theory of knowing and learning to machine learning (ML) and hope that my comments will support the efforts of Markus Nowak, Claudio Castellini and Carlo Massironi in continuing this promising line of research.

« 2 » In the field of assistive robotics for limb amputees, electromyographic signals generated by muscle activity in the remaining upper limb are used as input data for a machine learning (ML) system; the system should then produce control commands for a prosthetic arm/hand accordingly in order to let it perform the desired action (§33).

« 3 » Unfortunately, this so-called upper-limb myocontrol, after 40 years of research, is still failing (§34) with rejection rates of up to 75%. As a means of improving such systems (smart prosthetic arm/hand control systems), the authors of the target article suggest (§32) developing traditional ML to form an *interactive* machine learning (iML), which allows for system updates whenever its actions are unsatisfactory (§§21f). But this poses new problems, which require appropriate conceptual tools, in particular, a coherent conceptual framework about interactivity. This is where the authors anticipate that radical constructivism (RC) could help (§23), especially through its concepts of experiential reality (§15), learning as a constructive activity (§16), viability (§17), assimilation, scheme theory, accommodation and equilibration (§30).

« 4 » The application of RC to iML – so called *RC-framed iML* – for the task of upper-limb prosthesis is expected to provide useful insight into how to design the interactive prosthesis of the future (§89). The authors are convinced that their approach has the potential to improve human-robot interaction. Thus, they propose to shift the attitude towards ML from a realist to a radical constructivist attitude, as defined by von Glasersfeld (§13). They see their draft of an RC-framed iML presented in the target article, as an attempt at opening a discussion between the RC community and the ML community (§26).

« 5 » Applying RC to ML requires us to dive very deeply into radical constructivism and clarify its fundamental concepts. So, I will look at three fundamental concepts used in what the target article calls a "tentative framework" (§26) about "interactivity" (§23) and will try to dive deeper into them.

A | The construction of experiential reality

« 6 » Nowak et al. mention this concept and quote von Glasersfeld (1995: 58f) as a reference where it appears as a section title. I will highlight the essential parts of this section by not only repeating the same formulation but also by reformulating and extending them in my own terms.

« 7 » Humans, as infants and later as adults, can construct the reality they experience for themselves. As infants, humans develop the basic concepts that constitute the essential structure of their individual experiential reality, without needing a specific physical structure to exist in its own right as a *corresponding* structure.

« 8 » For example, let us look at the development of the notion of the "object" in a human infant. In phase 1, the infant coordinates sensory signals recurrently available at the same time in its sensory field (the "locus" of raw material that Immanuel Kant called "the manifold") and establishes by that many different object concepts; these object concepts are like operational routines for constructing the formerly constructed objects of interest again at a later point (a ball, a face, a cat, etc.) whenever suitable sensory components are available. The notion of "object" in general, then, is whatever the mind constructs *as common* to all these routines (a kind of abstract, generalised, operational routine) due to a principle of efficiency, implemented like in perception by means of "preferred paths" or "sequence patterns" (de Bono 1991: 81f; de Bono 1992: 10f). Later, in phase 2, the infant becomes able to run through such operational routines even when no suitable sensory components are available in its sensory field; in this case, the infant executes a conceptual coordination of a previously constructed object; it produces a *re-presentation* (written with the hyphen as a reminder that this term means a repetition, a replay, a re-construction from memory, of a past experience, not a picture of something in a mind-independent world).

« 9 » Thus, I do not agree with Nowak et al. when they say that the agent tries to "*organize perceptual objects*" (§15). Rather, I would avoid both "perceptual" and "objects" and say that the agent "organises a sensory field," conceived as the raw material that Kant called "the manifold," in which there are no objects unless we construct them. And when we have constructed them, I would not assign them to the sensory field but rather to our experiential reality, and there to a process that operates at a higher operational level. It is similar to looking at the skies on a clear night: you can only see an ordered pattern of stars, even a constellation, if you organise the single stars (the signals in your sensory field) by selecting some and connecting them, thus *constructing the pattern* in your mind rather than perceiving it (Glasersfeld 1999: 12; Bettoni & Eggs 2010: 133).

« 10 » Moreover, the essence of a "very radical-constructivist concept" here is not dealing with "'perceptual' data" (§15) but that the "object" as a generic concept, as a conceptual structure (and later many others), is constructed by organising a sensory manifold in many different ways and later by abstracting what is common to these previously constructed conceptual structures.

B | Learning as a constructive activity

« 11 » This concept used in the target article (§16) references an early article by von Glasersfeld (1983) of the same title. But I would not say that this early article presents "*matching 'perceptual' patterns*" as a foundation of RC. Since the fundamental epistemological principle of RC is "fit" not "match" ("viability" not "correspondence"), I would suggest avoiding the use of "match" altogether, even when it refers to sensory patterns or conceptual structures and not to pictures of the physical world.

« 12 » An elementary form of learning requires two components (Glasersfeld 1995: 152f):

- something like a memory,
- the ability to compare two signals, a present one and a goal-signal that constitutes a reference value.

Once these requirements are met, the preconditions of inductive learning are satisfied. In the event of a perturbation, all that is further needed for this elementary form of learning to occur is a rule or principle that leads the system to repeat actions that were recorded as successful in its past experience (see also de Bono 1991: 42f), thus

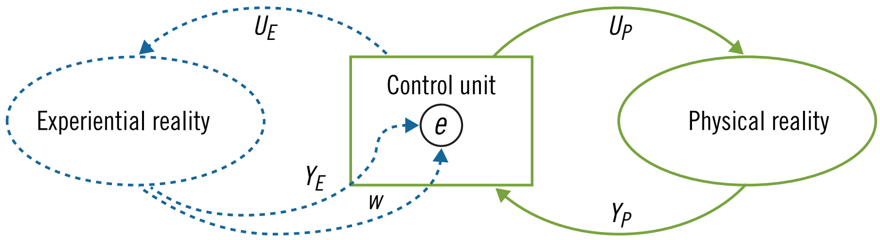

Figure 1 • The cybernetic model of viability: A coupled system of two processes controlled by one control unit. Abbreviations: Y = controlled variable; w = set point variable; e = control deviation; U = manipulated variable; index E = experiential reality; index P = physical reality.

reducing or eliminating this kind of new perturbation.

« 13 » Although the interactions the subject has had with the world shape what will be the result of new interactions (§18), the previous knowledge that they provide is not enough for the re-cognition of a certain situation (§19; Glasersfeld 1995: 65). In fact, the sensory field provides vastly more signals than those needed for its segmentation. The organism must therefore always actively select which signals to use in order to construct either a known or a new pattern that will trigger a particular scheme, so that the pattern can be assimilated. How can the agent do this active selection? I agree with von Glasersfeld (1995: 78f) that Ceccato's idea of an attentional system (Ceccato 1964) that produces successive pulses of attention and has the ability to form combinatorial patterns of attentional moments, can provide a model of how the mind actively selects signals in the sensory field. These pulses of attention, which I have called "attentional quanta" (Bettoni 2018), also constitute the operational structure of abstract concepts (Glasersfeld 1995: 167f). Could Ceccato's attentional system also be implemented in the ML system for enabling it to do the needed active selection?

« 14 » Whenever a scheme is activated and the triggered activity does not yield the expected result, the discrepancy between expectation (reference value) and the experienced result creates a perturbation in the system. This perturbation is equivalent to a variation of the input into a controller unit of a control loop with negative feedback (cybernetics, control engineering). It is a novel kind of perturbation; it is not associated with a specific sensory pattern or with a specific scheme and may lead to an accommodation, an adjustment of the scheme or the formation of a new one. In this way, assimilation and accommodation enable an agent to learn.

C | The viability of conceptual structures

« 15 » I agree that we cannot "build a *real* model of this world" (§17) but I disagree with saying that we can "build a viable representation of it" because, again, our conceptual structures cannot be said to represent a real mind-independent world. They merely fit with our own experience and they are viable as means for consistently organising our experience (Glasersfeld 1983).

« 16 » In order to dive deeper into the concept of viability, I suggest making use of the language of cybernetics and control engineering. This allows us to illustrate the concept of viability by means of a *system model* (see Figure 1) where we have *one* control unit that *controls two* process units; it is a very peculiar architecture of a coupled control system with two fundamentally different processes and hence two fundamentally different, but coupled, control loops.

The control loop of physical reality

« 17 » On the right-hand side of the diagram, I differentiate between reality as a physical controlled system or process, the person as its controller and two interactions between these two units: the physical effect of a person on reality (controller output, manipulated variable U_P) and the physical effect of this reality[1] on a person (controller input, controlled variable Y_P).

« 18 » The controlled variable Y_P only affects the person in the form of a manifold (Kant 1966: B 102; Glasersfeld 1995: 40f), i.e., in an unstructured manner. In the diagram, this is indicated by the fact that the arrow ends at the periphery of the control unit and does not penetrate into the inner circle, like the other variables.

The control loop of experiential reality

« 19 » On the left-hand side of the diagram, I differentiate between the experiential world as the entirety of the experiences acquired by a person (her knowledge base) and the person as the controller in the form of a separate unit; this separation is purely heuristic in nature for illustrative purposes. In this model, I also assign to the experiential world the role of a controlled system, but a conceptual (conceptually constructed) rather than a physical controlled system.

« 20 » There are three interactions between these two units here: the conceptual effect of a person's control unit on her experiential world (manipulated variable U_E) and two conceptual effects of the experiential world on the person's control unit. The set point variable w corresponds to the goals, intentions and expectations. The controlled variable Y_E is somewhat more complicated: a person takes the controlled variable Y_P, transforms it into thought content (manipulated variable U_E), seeks to integrate this into her experiential world (assimilation, accommodation etc.) and ends up with the controlled variable Y_E.

« 21 » The control deviation e is formed from a comparison between the set point variable w and the controlled variable Y_E; this produces a binary variable e, which provides information as to whether or not there are any obstacles in the way of pursuing the goals, i.e., whether or not the current state can be deemed *viable*. If the manipulated variable U_P has led to a solution or generates any concepts that are either compatible with existing conceptual structures (lack of contradictions) or in harmony with conceptual structures that others regard as viable, then in the control unit we will obtain $e=0$, i.e., the current state will be considered viable and will be reinforced.

1| By "physical reality" I mean the world of constraints in which organisms live (Glasersfeld 1983) and by "physical effect" I mean variations in the sensory field due to those constraints.

Conclusion

« 22 » Diving deeper into concepts such as *the construction of experiential reality* and *learning as constructive activity* ensures that the development of an RC-framed iML will be more consistent with RC. Furthermore, due to the central role assigned to interactivity by an iML approach, the double-loop model of viability presented here could become the starting point or foundation for developing the missing "coherent conceptual framework about interactivity" that ML needs (§23). Here the model deals with a *human-world* interaction, where the human is the active agent and the world provides constraints. In ML the roles are swapped: we have to model an *ML-human* interaction, where the ML system is the active agent and the constraints are provided by the human (§30).

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A Sociocultural Perspective for Learning Loops

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> Upshot • I point out that from a socio-cultural perspective, repeated experiential interaction loops are not enough for constructing new context-dependent knowledge: the loops must be grounded in specific social practices, which are either culturally or historically situated. Also, to tightly connect human user and interactive machine-learning system, triple-loop learning needs to be used as well as criteria for validating an expectation's confirmation.

« 1 » The improved interaction between users and learning systems in interactive machine learning (iML) needs a better understanding of how end-user involvement impacts the learning process (Amershi et al. 2014). To contribute to the discussion that Markus Nowak, Claudio Castellini and Carlo Massironi have opened, I want to highlight some properties of this interaction.

« 2 » Gregory Bateson (1979: 78) pointed out that one cannot hear the sound of one hand clapping. Likewise, the contributions of the human and the iML system to solving these problems cannot be decoupled. Thus, in iML we have to put the "human into the loop" (Holzinger 2016) to enable what neither a human nor a computer could do on their own.

« 3 » A conventional machine-learning (ML) system can be instructed with ever more examples when learning a stationary process (§12). Human behavior, however, is non-stationary (§29) and biomedical data sets are full of uncertainty and incompleteness (e.g., missing data, noisy data, etc.), which makes the application of conventional ML difficult or even impossible (Holzinger 2016).

« 4 » Since a human and iML system forms a tight coupling, some form of reflexivity is required to take into account the relationship that includes both elements as a part of it. As Erving Goffman (1974: 85) states, "a reflexive element must necessarily

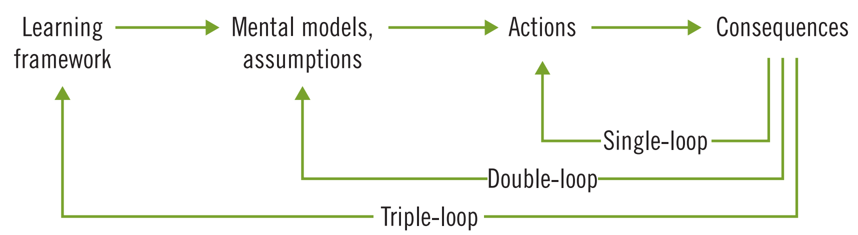

Figure 1 • Learning loops (Modified from "Modes of organizational learning" by Soren Eilertsen and Kellan London, https://le2oa.wikispaces.com/file/view/Modes+of+Organisational+Learning.pdf)

be present in any participant's clearheaded view of events; a correct view of a scene must include the viewing of it as part of it."

« 5 » What kind of relationship do we have to take into account if every description implies an observer who describes it (Foerster 1981: 258)? Obviously, reflexivity is not confined only to our observed interaction between human and iML system, but extends to a different level that also includes us as knowing subjects. For example, in §47ff the authors build a psychological context of interaction rules and reciprocal roles for the human – reassuring that the prosthesis learning ability was "only in its infancy" – which also involves readers who identify with this parental role.

« 6 » We can find another example of reflexivity in §37, where the authors claim that iML, based on radical constructivism, is superior to conventional realist ML. But who is the knowing subject in the experiment described afterwards (§§38ff): the iML system (here the learner) or the human (here the user) who adopts a non-realist theory of knowledge? Or both? The interaction loops increase the opportunities for users to impact the learner and, in turn, for the learner to impact the users (Amershi et al. 2014).

« 7 » Can we assume that the human, while providing feedback to the iML system, is developing a better awareness of her knowledge constructs? Does the iML system build on cultural knowledge thanks to the feedback provided by the human? Can the human and iML system create, together, new knowledge outside a social context where distances, shapes and sizes are culturally defined?

« 8 » An iML system can be conceived as a constructivist system that generates a certain kind of knowledge through experiential interaction loops (Sarkar 2016). This is how the prosthetic hand learns movements, i.e., by means of acquiring correct examples and feedback (§57ff). However, I claim that repeated experiential interaction loops are not enough for constructing new knowledge: the loops must be grounded in specific social practices, which are either culturally or historically situated. These practices are governed by constraints, in which people engage with "objects" or other constructed entities, understood in terms of apparently independent, decontextualized properties. As Peter Berger and Thomas Luckmann (1967: 61) observed, humans are capable of producing a world that they then experience as something other than a human product (see also Packer & Goicoechea 2000).

« 9 » So, assuming a sociocultural perspective, activities are characterized as practices of a community. There are many different ways of moving a hand, because, as Goffman observed:

> "[…] while the substratum of a gesture derives from the maker's body, the form of the gesture can be intimately determined by the microecological orbit in which the speaker finds himself. To describe the gesture, let alone uncover its meaning, we might then have to introduce the human and material setting in which the gesture is made." (Goffman 1964: 133)

« 10 » In order to execute an action such as grasping a cup of tea or repairing a bicycle, in addition to movements and validated procedures, does an iML have to learn something about the "frame" (Goffman 1974), i.e., the human and material setting in which the action has to be executed? (Q1). For the experiment described in §§38ff this means the prosthetic hand's activity requires a rich context where meaning can be negotiated, and understanding can emerge and evolve (Sarkar 2016).

« 11 » In order to establish a tight coupling between a human and her iML system, we need triple-loop learning that is able to transcend single- and double-loop learning:

- Single-loop learning occurs when the system learns new skills and capabilities through incremental improvement: the system assimilates the information that it can already recognize. Errors are detected and corrected by a human agent, who acts without perturbing the system (see also, in §53, the evaluation phase of experiment 0).
- Double-loop learning is reflective and occurs when errors are detected and corrected, and expectations, and/or assumptions are called into question and challenged. As Nowak et al. report in §59ff (Experiments 1 and 2), when dealing with complex, non-programmable issues, the iML system was perturbed. The concept of perturbation refers to a stimulus that does not conform, or gently subverts, the expectations and mental model of the users, forcing them to construct new knowledge in order to accommodate this experience (Sarkar 2016). Error detection still occurs, but the iML system is required to change its assumptions and mental model to try to understand the "connecting structure" (Bateson 1979) that helps to detect these errors.
- Triple-loop learning involves a learning framework where "the subject learns the context of the action and how these actions are connected to the world" (Lutterer 2012). Here we must include the context, because movements and mental processes are formed in and through participation in specific social practices, which can be both culturally and historically situated (Packer & Goicoechea 2000). Learning to move a hand is also, and always, a learning of context (Bateson 1972: 293): activity is dialectically constituted in relation to the setting (Lave 1988: 151).

« 12 » Figure 1 shows how the relationship between the three loops of learning can be depicted. Each successive loop extends beyond the boundary of, and includes, the previous loop.

« 13 » Coming back to the experiments in the target article, positive feedback or confirming a prediction strengthens the experiential reality that the human and iML system are constructing together. In §52, during model building, all the instantiations are supposed to be "good" signals. In other words, the human confirms the expectations of the system, which was building its own "reality." Furthermore, during model testing, whenever a particular prediction concerning an action or reaction of the other turns out to be corroborated by what the other does, this strengthens, in a different loop, the experiential reality and the mental models that both are constructing together.

« 14 » Since prediction is different from explanation, in §59 when the system received negative feedback, I claim that the iML system was perturbed in a twofold manner: because its expectations did not fit and because its assumptions were not confirmed.

« 15 » Likewise, by means of perturbation, the iML system was stimulated by the human to construct new knowledge, for example, some criteria for validating an expectation confirmation, or using our previous terminology, both are construing concurrently a new shared learning framework.

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Are Our Limbs Agents that Need to Estimate Our Intentions?

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> Upshot • I argue that the authors miss an important distinction between realism and representationalism. Because of this, their diagnosis of the current state of machine learning is valid, but for the wrong reasons. As a consequence, their approach to upper limb prosthetics may not be a step in the right direction.

« 1 » The target article constitutes a positive and very welcome contribution to a problem that has been plaguing human-machine interaction since its inception, namely prosthetics. Although Markus Nowak, Claudio Castellini and Carlo Massironi introduce their reflection as being about machine learning (ML) in general, the particular case of prosthetics is of such significance that the authors' ideas about the latter deserve as much scrutiny as their general concern with machine learning. This commentary will thus focus both on the authors' contention with what they take to be the realist stance towards ML and on the particular study they chose.

« 2 » Nowak et al. start by noting in §10 that ML tends to be used currently as a "number-crunching black box" the function of which is simply to yield useful mappings from input to output according to the designers' interests. I agree with the authors' lament that, very often, the meaning of the mappings and the processes going on in the machine are opaque to the designers, who do not seem to care. A quick and shallow rebuttal to this could be: "So what? There is nothing wrong *a priori* with having a completely instrumental attitude towards a particular computational tool." But the authors go further and they argue that whenever the model fails *in practice* it is indeed because of that theoretical attitude just mentioned, in other words, ML models are being limited because their designers are not paying attention to deeper conceptual issues. Examples of such limitation are a model's failure to produce the expected output or, as in the case of prosthetics, the dramatic and systematic failure to produce a satisfactory coupling between human and machine, as exemplified by the painful figure of 75% rejection rate the authors rightly mention. This part of their assessment and critique seems accurate and there does seem to be a connection between the practical shortcomings of ML and its conceptual foundations. However, the rest of the authors' diagnosis and subsequent suggestion of a solution may not be so accurate.

« 3 » The main contention here is that Nowak et al. conflate two different things in their critique, to wit, realism and representationalism. To be fair, they are not the first ones to do this conflation, which can be traced back at least to Francisco Varela, Evan Thompson and Eleanor Rosch (1991) and perhaps even as far back as Edmund Husserl's phenomenology. In a nutshell, the argument of Nowak et al. is that ML fails because it is designed to naively attempt to build a statistical model of an external world, but for any modeling of "reality" to be accurate, the sample input – the examples to which the model is exposed – needs to be exceedingly large. We can already notice here that any reasoning that reaches this conclusion is faced with a choice point. We can either blame the realist attitude of believing that there is an external world that the model needs to reflect, *or* we can blame the very attempt to *model* such a reality. Perhaps, and this option is rather ignored by the authors, there *is* a "naive" external reality, but the right approach to learning and knowledge in artificial intelligence, at least if the goal is to approach human performance or to make interaction with humans possible, is not that of trying to *represent* the world through a model, but rather to *fit* the world. Just like the woodpecker's beak does not represent the tree – the beak is definitely not a *model* of the tree, yet it is a perfect *complement* to the tree for the purposes of the woodpecker (e.g., drilling a hole and catching termites) – ML systems could benefit from not attempting to represent their targets but to fit them in some meaningful way. The problem, in short, is not trying to represent *the world*, but rather trying *to represent* the world.

« 4 » Interestingly, Nowak et al. seem to have a tacit understanding of this problem, but I suggest that, because they fail to discern between realism and representationalism, they aim their criticism at the wrong target. For instance, following Ernst von Glasersfeld they claim §17 that "the value of an idea of the world is measured in terms of fitness to achieve a specific goal […], not in terms of the correspondence between the idea and a mind-independent reality." But we can readily see in this statement that if the value of the idea resides in its ability to contribute to the achievement of a specific goal, then the content of the idea itself must be about achieving that goal. *That*, I suggest, should be the reason why the authors contrast fitness with "correspondence" and *not* the belief that there is indeed a mind-independent reality. Again, the woodpecker is successful in drilling a hole in the tree and catching insects for its nourishment, not because it refuses to treat the tree as "bird-independent," but because the beak and the muscular forces it applies to the tree adequately fit the latter's material properties for the purpose of drilling a hole in it. Bird and beak are in *direct* contact with the tree, they are both complementary and fit each other as mathematical duals (Gibson 1979; Shaw, Kugler & Kinsella-Shaw 1990). It is not the tree, or the external world for that matter, that needs to go, but mediational states between it and the subject (or learning machine).

« 5 » Furthermore, if we give up realism, it is virtually impossible to make sense of what the meaning of constructivist "perturbations" to the system are. If perturbations are mind-dependent and do not come from an external reality, then what is the system adapting to? But a deeper question actually addresses the authors' own concern about the meaning of what ML models do and the origin of that meaning. Perturbations must have an independent origin at least partially if they are to be meaningful to the system and effective in driving it towards improved performance. But according to Nowak et al., following their understanding of radical constructivist theory, "[*a*]*ll* these processes" must be subjective and internal – including the perturbation §19 (emphasis original). This idea is not, however, that an idealist mind is generating ideal perturbations to its own ideal perception. The issues with such forms of idealism are well known. We must rather interpret that wherever the perturbations come from, they are being shaped, interpreted, idealized somehow by the subjective agent, and they only make sense as perturbations to the agent from that subjective perspective, product of her own making (or construction). Internal conceptual schemata – the subject's pre-knowledge – are the usual posit since Kant, although they have not been without detractors (see, e.g., Donald Davidson's well-known 1974 paper). But then again, even these schemata must have an origin and we cannot posit more regressing subjects and their own schemata to account for them. It is revealing that the ethologist does not have this problem. Bird's beak and tree form a closed system, they evolved together and interact straightforwardly perturbing each other. No pre-knowledge or schemata are needed, Jakob von Uexküll's seemingly constructivist concept of Umwelt notwithstanding (Uexküll 2010).

« 6 » Thus, it seems that the authors' move towards radical constructivism as a solution to the current state in ML is a right step, although in the wrong direction. It is a move towards more reliance on representation as intermediate subjective constructs, and that could be precisely what is crippling progress in statistics-based ML. In the following I will address the point that, as a consequence of the authors' failure to identify representation as the origin of the issues faced by ML, their proposal for prosthetics misses the target too.

« 7 » It is very surprising to find no mention at all of embodiment in the target article. Yet upper-limb prosthetics constitutes a proverbial problem of embodiment. The challenge is to make an external object part of the patient's *body*, as the lost limb used to be. But notice that our healthy limbs are the exact opposite of an autonomous subjective agent trying to construct an internal model of ourselves where all the interactions with us are "user-independent." Such an idea is actually strikingly counter-intuitive. It is one thing to acknowledge that, because of the limitations of prosthetics that need to be coupled to a body *ex novo*, unlike our limbs, which grew with us and have interacted with us since our fetal stage, one needs to adapt the prosthetic limb to the body in a very short time and thus some form of ML, interactive or otherwise seems necessary as a practical necessity. It is another thing, however, to approach this problem, which is actually an unfortunate contingency, by making the disconnect between limb and body even deeper, yet that is precisely what the radical constructivist approach to prosthetic adaptation appears to imply. The ideal goal would be to be able to *grow* a new limb, as salamanders do, and let the interactions between neural, muscular and bony tissues adapt to one another during the growth process. The end result would be an *embodied* limb, one that is part of the subject, directly coupled to all the other limbs, nervous cells, etc., and certainly not anything that resembles a *separate* agent that interacts with us through intermediate mental schemata.

« 8 » Moreover, some of the negative consequences of Nowak et al.'s second experiment, namely the patient's painful fatigue, are a cruel reminder that the perturbations a subject needs to deal with are quite "real," for lack of a better term. The prosthetic is a massive body, and the earth is pulling on it through gravity. These are external constraints that the learning process taking place on the side of the prosthetic limb simply cannot anticipate or cope with. From its agential, subjective point of view, it is all a matter of guessing the agent's intentions, constructing a model, a predictive schema of EMG patterns and adapting to its constraints. Little does it know that there is a concrete living being on the other side struggling to produce movements by generating the right muscular contractions against torques and discomfort. But these muscular contractions not only need to deal with gravitational forces, they are also not *meant* to serve as signals for an ML-based prosthetic limb to interpret – we do not move our healthy limbs through vicarious muscular contractions and high-amplitude electric potential at the surface of our muscles. We move our healthy limbs by fitting our intentions to the external non-muscular forces, but our intentions are embodied and include the limb itself as well as the external force fields (Merleau-Ponty

1962). By applying the authors' version of a radical constructivist ML solution to prosthetic limbs, this embodiment is lost, and what was a direct, high-bandwidth, logically shallow flow from intention to motor performance in the healthy coupling is interrupted by representations (Neumann 1958; Haugeland 1998; Dreyfus 2002). The result is qualitatively the same as it was with so-called "realist" ML, because both the latter and what the authors take to be a radical constructivist ML remain representational. Restoring the functionality of a lost limb, given the loss of its deeply intimate coupling with the rest of our body and nervous system, is extremely difficult. However, progress will hardly be made by establishing even more subjective discontinuities between patient, prosthetic limb and world. On the contrary, what is needed is a blurring of the boundaries between them as much as possible and an acknowledgement of the overwhelming influence of material constraints such as external forces, which are more than meaningless perturbations, and can also be an active part of the coordination of movement (Bernstein 1967).

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Authors' Response

Radical Constructivism in Machine Learning: We Want More!

Markus Nowak, Claudio Castellini & Carlo Massironi

> Upshot • Our commentators' very constructive criticisms point out a number of weaknesses in the design of our experiment, and offer insight into how such weaknesses might have led to the poor results of the experiments. We summarize the suggestions, which point in a few precise directions, and outline how we will try to implement them in the near future.

« 1 » While there seems to be general agreement among our commentators that framing interactive machine learning (iML) in radical constructivism (RC) is a valid contribution to research in machine learning (ML) and could improve the situation of myocontrol, they also point out that the experiment might have been too simple, and for that reason it has failed to fully prove our point. They all suggest improvements to both the setup and the experimental design, and it is fascinating to note that similar suggestions, or at least suggestions that hint at similar directions, come from researchers who are experienced in very different fields. We feel inspired and will continue on this path, extending it further.

As simple as possible, but not simpler

« 2 » Our working assumption was that rethinking myocontrol through RC would give hints and suggestions for the design of the upper-limb prosthesis of the near future. This intuition stemmed from our own previous work in incremental/interactive learning applied to myocontrol, for which RC seems to provide an ideal theoretical framework, as it is rich in ideas to be applied in practice. So, we put in place a simple experiment with three variants, each variant being "more radical constructivist" than the previous one, hoping that the ideas based upon RC would have led to a clear improvement in performance.

« 3 » This has turned out to hardly be the case. So, was our working assumption correct? The consensus emerging from the open peer commentaries that we received seems to indicate that it was. But at the same time, the general feeling is that the experiment was too simple with respect to medical applications, and that this excess simplicity has blurred the distinctions between the three experiments almost completely. Once again, Albert Einstein's motto, which we have cited already in §40 of our target article, is key: if you simplify too much you lose sight of the problem you are trying to solve, and you might end up finding an inadequate solution.

Did we simplify too much?

« 4 » **William Craelius**'s statement "The experiments were elegantly designed and executed, but the results rather disappointing" (§6) is a perfect synopsis of our work. His first criticism refers to the lack of purpose in the tasks and therefore the lack of motivation for the participant. Although we fully agree with his remedy of shaping the tasks in a game-like manner, some studies, such as one by Ludger van Dijk et al. (2016), point out that improvements achieved in games using control modalities based on muscle signals do not necessarily transfer to improvements in prosthetic control. **Craelius** himself, with reference to Yungher & Craelius (2012), states that "a significant improvement in speed of 15% was achieved after 30 trials with their virtual assistive robot; controls, in contrast, showed negligible improvement with their prosthesis" (§8). Therefore, we chose tasks or actions that reflect what a user would do with her prosthesis, although a repetitive task might lack excitement for her.

« 5 » **Craelius** issued two more criticisms. Firstly, he pointed out that there was a lack of disabled subjects in our study. This is undeniably a shortcoming, as is the low number of participants, which we will amend in the mid-term future. Secondly, **Craelius** stated that the residuum can accommodate a larger number of sensors than a sound limb. In our experience, though, the opposite seems to be the case. Still, we agree that an increased number of sensors can lead to richer information about muscle activity. When it comes to placement, our approach is to cover the whole circumference of the residuum rather than to target specific muscles. Doing so is our way of dealing with the mentioned radical muscle and tendon rearrangement and disruption of synergies among them.

« 6 » This last criticism is shared by **Richard Weir**. His lament against the non-patient-centric view of the ML community (§§1f), of which we are part and parcel, is totally well founded. For starters, electromyography has a number of well-known downsides, and the scientific community has been suggesting for almost a decade now that novel ways to detect muscle activity in a residual limb should be conceived and tested (Castellini 2014). We ourselves are active in this field so we could not agree more on this, but this was not the focus of this work. Anyway, we acknowledge that using too few sensors (possibly of the wrong kind) would inevitably make sophisticated interaction useless – a view that all our commentators seem to share. Improving the sensors should be synergistically coupled with the RC-framed approach to iML. Furthermore, the lack of feedback is an issue that is present in the entire field of myoelectric control. So far, no clinical system (besides body-powered hooks) provides relevant feedback to the wearer. As yet, we ourselves have investigated this topic very little.

« 7 » Again, we fully agree with **Weir** (§13) that the "ML algorithm […] is not the determinant for success"; we rather argue that the ML method, whatever it is, needs to possess certain characteristics – at least incrementality, which leads to interactivity. The pilot study presented here makes intentional use of a standard method, briefly mentioned in §40 of our target article. We solely used the low-pass filtered rectified amplitude of the signals. (For further details on the method we refer the interested reader to Gijsberts et al. 2014.)

« 8 » Furthermore, our work does not in any way challenge the effectiveness of the standard two-sites-of-residual-activity myoelectric system widely used in clinics. Pattern recognition (PR) potentially solves the issue of switching commands required in two-sites control, leading to "natural" control. From our experience, not having to rely on these commands would be a very welcome advancement for the prosthesis wearers; however, PR comes at a price, one of which being the lengthy initial calibration process. But the work that we present in our article is aimed at tackling exactly this problem: we want to eliminate the need to train all possible actions, in all required postures, for several times at once, in the beginning.

« 9 » This is exactly where interactivity leads to a better combined performance of wearer and prosthesis, following the imperative: "do not collect *more* data, rather collect *better* data." In Experiment 2 for example, we started with an empty model (no training data at all) and updates only occurred when, and if, required. Repeating all gestures in all postures, as mentioned by **Weir** ("moving from one posture to another may result in overlapping muscle activity patterns," §10), is exactly what the RC-framed iML should avoid.

« 10 » All in all, the picture starts to emerge – myocontrol could be a paradigmatically *holistic* problem: either you solve all its aspects at once, or you will not be able to solve it at all. Therefore, all suggestions we received (design more engaging tasks; improve the sensors; improve interaction; and give feedback) need to be taken into account collectively. **Peter Cariani**, starting from his conceptual background and his research agenda as a physiologist, gets to a similar conclusion. He compares the physiology of motor control under natural vs. experimental conditions and suggests enriching the human-machine interaction by adding more *observables, actions,* and *feedbacks* available to both the machine and the human, such as incorporating proprioceptive and tactile feedback signals from artificial hands and arms into prosthetic controllers. The grand goal is that of reproducing the wealth of bidirectional flow of information taking place in intact subjects: a large number of sensory channels, significant proprioceptive feedback, tactile feedback, copies of the command signals that are activating muscles.

« 11 » Regarding **Cariani**'s questions about the usage of the normalised root mean squared error: the nRMSE was used only as an *a posteriori* inter-subjective measure of the accuracy of the system and it played no role whatsoever in the selection of the training data. The training feedback was always and only that provided by the subject (Q1). We confirm that in this case the feedback could have easily been replaced by a threshold posed on the nRMSE itself (Q2), which is what usually is done in the field of myocontrol – for instance when using the Target Achievement Control test as described by Ann Simon et al. (2011). Actually, from the point of view of the engineer, this is a very unusual characteristic of our experimental protocol: to employ a subjective judgment to determine whether a task was successful or not, instead of an inter-subjectively verifiably measure. We ourselves have used such measures in the past.

« 12 » Particularly fascinating in **Cariani**'s commentary is the idea that the initial choice of observables, actions and feedbacks determines a cognitive "cage" in which the ML system is trapped – and since we have had no chance so far to design a ML system that evolves its own sensors and actuators, the cage remains as it is for the rest of the experiment and plays a key role in its outcome.

« 13 » There is an unfortunate practical implication of **Cariani**'s idea: any prosthetic system endowed with insufficient hardware will *never* get to a satisfactory level of integration and performance, no matter how smart the ML method and/or the interaction schema is – one more hint at the holistic nature of myocontrol. Things are made even worse by the extremely high acceptance threshold in the field, as pointed out by **Weir** (§3), who, by the way, also touches upon this "cannot-neglect-the-hardware" conundrum when he says:

> "It is the limited number of control sites and the associated limit on the number of controllable DoF [degrees of freedom] that led investigators to explore other means of acquiring and using multi-DoF control schemes such as ML. Users certainly want more DoFs, but not if it is a hassle." (§5)

« 14 » **Cariani**'s view is that human-machine interaction can be seen as two *adaptive, purposive percept-coordination-action* *systems*, in which the data collection should be even more dependent on the evaluative feedback to the machine than in our simple experiment. Here too, we could not agree more.

Attention and culture

« 15 » More ideas and suggestions, particularly focussing on the interaction, are to be found in the remaining commentaries. Starting from an exquisitely radical constructivist perspective and adopting our research agenda as a working hypothesis, **Marco Bettoni** offers some useful linguistic/conceptual suggestions and two operational models. **Bettoni** suggests operating a conceptual switch from organising *perceptual* objects to organising a *sensory* field and then, after having constructed a conceptual object, assigning the object not to the sensory field but rather to the "experiential reality" (a higher operational level). We definitely agree with his suggestions, particularly with the request to avoid using the word "match" altogether, "even when it refers to sensory patterns or conceptual structures and not to pictures of the physical world" (§11).

« 16 » From a sociocultural perspective, **Marco Guicciardi** argues that human-machine interaction loops must be grounded in specific social practices, culturally and historically situated (repeated experiential interaction loops are not enough). In designing our experiments, we have already tried to enrich the socio-cultural dimension with respect to a classical experimental setting by working on the dimension of meaning, and on the mutual roles of human and machine: designing meanings for the interaction and inventing reciprocal roles for human and machine.

« 17 » Still, **Guicciardi** goes even further, suggesting giving the iML system the capacity to grasp the "frame" of the interaction (the rich context), to uncover the meaning (culturally and historically situated) of a gesture. His suggestions are twofold: we should give the iML system the capacity to grasp the sociocultural context of the interaction; at the same time, we should enable the participant to be more aware of the iML system's knowledge constructs; and both should have the capacity to create together new knowledge outside the original social context where distances, shapes and sizes are culturally defined. In order to provide at least a partial answer to his Q1, one initial move in this direction is to diversify and enhance the sensor modalities available to the iML system – not only to have more sensors of a specific kind, but also more different kinds of sensors relating to different kinds of data. For instance, there could be feedback from the device, environmental information, a more articulated dialogue between the prosthesis and the participant and a skilled way of extracting information from it. In this sense, it is likely that the more data, the better, provided that the iML system is able to discern the relevant information from that which is irrelevant.

As salamanders do?

« 18 » Finally, **Martin Flament Fultot** starts from a non-representationalist conceptual background, *à la* "intelligence without representation" (Brooks 1991), mixing behaviorism and Maurice Merleau-Ponty's phenomenology. **Flament Fultot**'s research agenda is extremely different from ours:

> "The ideal goal would be to be able to grow a new limb, as salamanders do, and let the interactions between neural, muscular and bony tissues adapt to one another during the growth process. The end result would be an embodied limb." (§7)

As he clearly states, he is not interested in trying to build "anything that resembles a *separate* agent that interacts with us through intermediate mental schemata" (ibid), as we, instead, are.

« 19 » For instance, in §3, **Flament Fultot** suggests trying not to represent the world through a model, but rather to *fit the world just like the woodpecker's beak fits the tree.* But what is meant by *representation* here? In ML it is customary to do away with this concept by blurring the distinction between a representation and, for example, the weights of a neural network. These two positions do not clash with each other, rather they start from two completely different definitions of a representation. For instance, we agree with **Flament Fultot** about stressing the concept of fitting, but we are definitely not interested in equipping the iML system with the capacity to build a "true representation" of the world. Rather, our ideal iML system should just organize its sensory field to build its experiential reality (see **Bettoni**'s commentary and our response above).

« 20 » Surprisingly, there is a final point of strong agreement between **Flament Fultot** and us, and this is the concept of embodiment, or more precisely *having the prosthesis feel like a part of the patient's body*. This concept is slowly finding its way in the human-robot-interaction community, too, due to the intuition that control will improve as the user embodies the prosthesis. Such embodiment can only be realised via technologies that are not yet in sight, including extreme mechatronic dexterity, detailed feedback with sensory substitution, and close-to-perfect myocontrol. Given the current state of the art, for this experiment we have instead chosen to make the prosthesis a better, friendly, more responsive, *tool/buddy*, but in the future an upper-limb prosthesis will be used like a pair of glasses: don it and it works fine, doff it and go to sleep, don it again the next morning and it will work again just like yesterday – see **Weir**'s remark at §8. The road to embodiment is still very long, but we would like to see our attempt as a small step towards that goal.

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Combined References

Ajiboye A. B. & Weir R. F. ff. (2005) A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control. IEEE Transactions on Neural Systems and Rehabilitation Engineering 13(3): 280–291.

Amershi S., Cakmak M., Knox W. B. & Kulesza T. (2014) Power to the people: The role of humans in interactive machine learning. AI Magazine 35(4): 105–120.

Atkins D., Heard D. C. Y. & Donovan W. H. (1996) Epidemiologic overview of individuals with upper-limb loss and their reported research priorities. Journal of Prosthetics and Orthotics 8: 2–11.

Baschuk C. M., Hoeun P., Katzenberger L. M., Latour D. A., Passero T. & Tompkins E. J. (2016) Utilization of pattern recognition with patients initially contraindicated for myoelectric control of upper-limb prostheses. In: Proceedings of the first international symposium on innovations in amputation surgery and prosthetic technologies, Chicago IL: 79–81.

Bateson G. (1972) Steps to an ecology of mind. Chandler, San Francisco. Reprinted in 2000 by The University of Chicago Press.

Bateson G. (1979) Mind and nature: A necessary unit. E. P. Dutton, New York.

Berger P. & Luckmann T. (1967) The social construction of reality: A treatise in the sociology of knowledge. Anchor, Garden City NY.

Bernstein N. (1967) The coordination and regulation of movements. Pergamon Press, Oxford.

Bettoni M. (2018) Aufmerksamkeitsquanten: Bausteine autonomen und kreativen Denkens. In: Hug T., Mitterer J. & Schorner M. (eds.) Proceedings of the Ernst von Glasersfeld Centenary Conference. Innsbruck University Press, Innsbruck, in press.

Bettoni M. & Eggs C. (2010) Usercentred knowledge management: A constructivist and socialized view. Constructivist Foundations 5(3): 130143.
▸ http://constructivist.info/5/3/130

Brooks R. A. (1991) Intelligence without representation. Artificial Intelligence 47: 139–159.
▸ http://cepa.info/4059

Card S. K., Newell A. & Moran T. P. (1983) The psychology of human-computer interaction. Lawrence Erlbaum, Hillsdale NJ.

Cariani P. (1989) On the design of devices with emergent semantic functions. Unpublished PhD Dissertation, State University of New York at Binghamton, Binghamton, New York.

Cariani P. (2011) The semiotics of cybernetic percept-action systems. International Journal of Signs and Semiotic Systems 1(1): 1–17. http: //cepa.info/2534.
▸ http://cepa.info/2534

Cariani P. (2015) Sign functions in natural and artificial systems. In: Trifonas P. P. (ed.) International handbook of semiotics. Springer, Dordrecht: 917–950.

Castellini C. (2016) Incremental learning of muscle synergies: From calibration to interaction. In: Bianchi M. & Moscatelli A. (eds.) Human and robot hands: Sensorimotor synergies to bridge the gap between neuroscience and robotics. Springer, New York: 171–193.

Castellini C., Artemiadis P., Wininger M., Ajoudani A., Alimusaj M., Bicchi A., Caputo B., Craelius W., Dosen S., Englehart K., Farina D., Gijsberts A., Godfrey S., Hargrove L., Ison M., Kuiken T., Markovic M., Pilarski P., Rupp R. & Scheme E. (2014) Proceedings of the first workshop on peripheral machine interfaces: Going beyond traditional surface electromyography. Frontiers in Neurorobotics 8: 22.

Ceccato S. (1964) A model of the mind. Methodos 61: 3–75.

Childress D. S. & Weir R. F. ff. (2004) Control of limb prostheses. In: Smith D. G., Michael J. W. & Bowker J. H. (eds.) Atlas of amputations and limb deficiencies: Surgical, prosthetic and rehabilitation principles. Third edition. American Academy of Orthopaedic Surgeons (AAOS) Rosemont IL: 175–198.

Ciancio A. L., Cordella F., Barone R., Romeo R. A., Bellingegni A. D., Sacchetti R., Davalli A., Di Pino G., Ranieri F., Di Lazzaro V., Guglielmelli E., Zollo L. (2016) Control of prosthetic hands via the peripheral nervous system. Frontiers in Neuroscience 10: 116.

Connan M., Ruiz Ramírez E., Vodermayer B. & Castellini C. (2016) Assessment of a wearable force- and electromyography device and comparison of the related signals for myocontrol. Frontiers in Neurorobotics 10: 17.

Davidson D. (1974) On the very idea of a conceptual scheme. Proceedings and Addresses of the American Philosophical Association 47: 5–20.

de Bono E. (1991) I am right, you are wrong. Penguin Books, London.

de Bono E. (1992) Serious creativity. Harper Collins, New York.

Dreyfus H. L. (2002) Intelligence without representation – Merleau-Ponty's critique of mental representation: The relevance of phenomenology to scientific explanation. Phenomenology and the Cognitive Sciences 1(4): 367–383.

Englehart K. & Hudgins B. (2003) A robust, real-time control scheme for multifunction myoelectric control. IEEE Transactions on Biomedical Engineering 50(7): 848–854.

Fails J. A. & Olsen D. R. (2003) Interactive machine learning. In: Proceedings of the 8th international conference on Intelligent user interfaces (IUI '03) ACM, New York NY: 39–45.

Farina D., Jiang N. & Rehbaum H. (2014) The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges. IEEE Transactions on Neural Systems and Rehabilitation Engineering 22(4): 797–809.

Farrell T. R. & Weir R. F. ff. (2008a) A comparison of electrode implantation and targeting on pattern classification accuracy for prosthesis control. IEEE Transactions on Biomedical Engineering 55(9): 2198–2211.

Farrell T. R. & Weir R. F. ff. (2008b) Analysis window induced controller delay for multifunctional prostheses. In: Proceedings of the University of New Brunswick's Myoelectric Controls/Powered Prosthetics Symposium (MEC '08) Fredericton, New Brunswick, Canada: 13–15 August 2008: 225–228.

Fisher R. A. (1936) The use of multiple measurements in taxonomic problems. Annals of Human Genetics 7(2): 179–188.

Foerster H. von (1981) Notes on an epistemology for living things. In: Foerster H. von, Observing systems. Intersystems Publications, Seaside CA: 258–271.

Fougner A., Scheme E., Chan A. D. C., Englehart K. & Stavdahl O. (2011) Resolving the limb position effect in myoelectric pattern recognition. IEEE Transactions on Neural Systems and Rehabilitation Engineering 19(6): 644–651.

Fougner A., Stavdahl Ø., Kyberd P. J., Losier Y. G. & Parker P. A. (2012) Control of upper limb prostheses: Terminology and proportional myoelectric control – A review. IEEE Transactions on Neural Systems and Rehabilitation Engineering 20(5): 663–677.

Gergen K. J. (1978a) Experimentation in social psychology: A reappraisal. European Journal of Social Psychology 8: 507–527.

Gergen K. J. (1978b) Toward generative theory, Journal of Personality and Social Psychology 36(11): 1344–1360.

Gergen K. J. (1985) The social constructionist movement in modern psychology. American Psychologist 40(3): 266–275. ▸ http://cepa.info/4538

Gergen K. J. & Gergen M. (eds.) (1985) Historical social psychology. Lawrence Erlbaum, Hillsdale NJ.

Gibson J. J. (1979) The ecological approach to visual perception. Houghton, Boston.

Gijsberts A., Bohra R., Sierra González D., Werner A., Nowak M., Caputo B., Roa Garzón M. A. & Castellini C. (2014) Stable myoelectric control of a hand prosthesis using non-linear incremental learning. Frontiers in Neurorobotics 8: 8.

Glasersfeld E. von (1983) Learning as constructive activity. In: Bergeron J. C. & Herscovics N. (eds.) Proceedings of the 5th Annual Meeting of the North American Group of Psychology in Mathematics Education, Vol. 1. PME-NA, Montreal: 41–101. ▸ http://cepa.info/1373

Glasersfeld E. von (1995) Radical constructivism: A way of knowing and learning. Falmer, London. ▸ http://cepa.info/1462

Glasersfeld E. von (1999) How do we mean? A constructivist sketch of semantics. Cybernetics and Human Knowing 6(1): 9–16. ▸ http://cepa.info/1503

Glasersfeld E. von (2005) Thirty years radical constructivism. Constructivist Foundations 1(1): 9–12. ▸ http://constructivist.info/1/1/009

Goffman E. (1964) The neglected situation. American Anthropologist. 66(2): 133–136.

Goffman E. (1974) Frame analysis. An essay on the organization of experience. Harper & Row, New York.

Gorsic M., Cikajlo I., Goljar N. & Novak D. (2017) A multisession evaluation of an adaptive competitive arm rehabilitation game. Journal of Neuroengineering and Rehabilitation 14: 128.

Hahne J., Markovic M. & Farina D. (2017) User adaptation in myoelectric man-machine Interfaces. Scientific Reports 7: 4437.

Harré R. (1979) Social being: A theory for social psychology. Blackwell, Oxford.

Harré R. (ed.) (1986) The social construction of emotions. Blackwell, Oxford.

Harré R., Smith J. & van Langenhove L. (eds.) (1995) Rethinking psychological methods. Sage, London.

Haugeland J. (1998) Having thought. Harvard University Press, Cambridge MA.

Herberts P., Almström C., Kadefors R. & Lawrence P. (1973) Hand control via myoelectric patterns. Acta Orthopaedica Scandinavica 44: 389–409.

Holzinger A. (2016) Interactive machine learning for health informatics: When do we need the human-in-the-loop. Brain Informatics 3: 119–131.

Hudgins B., Parker P. & Scott R. N. (1993) A new strategy for multifunction myoelectric control. IEEE Transactions on Biomedical Engineering 40(1): 82–94.

Iturrate I., Chavarriaga R., Montesano L., Minguez J. & del R. Millán J. (2015) Teaching brain-machine interfaces as an alternative paradigm to neuroprosthetics control. Scientific Reports 5: 13893.

Jiang N., Dosen S., Müller K. R. & Farina D. (2012) Myoelectric control of artificial limbs: Is there a need to change focus? IEEE Signal Processing Magazine 29(5): 148–152.

Kant I. (1966) Kritik der reinen Vernunft. Edited by I. Heidemann. Reclam, Stuttgart. Edition A originally published in 1781, edition B in 1787.

Kuttuva M., Flint J., Burdea G. & Craelius W. (2005) Manipulation practice for upper-limb amputees using virtual reality. Presence 14: 175–182.

Lave J. (1988) Cognition in practice: Mind, mathematics and culture in everyday life. Cambridge University Press, Cambridge UK.

Lawrence P. D. & Kadefors R. (1974) Classification of myoelectric patterns for the control of a prosthesis. In: Herberts P., Kadefors R., Magnusson R. & Petersen I. (eds.) The control of upper-extremity prostheses and orthoses. C. C. Thomas, Springfield IL: 190–200.

Lock B. A., Simon A. M., Stubblefield K. & Hargrove L. J. (2011) Prosthesis-guided training for practical use of pattern recognition control of prostheses. In: MEC 11 Raising the Standard. Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium. University of New Brunswick, Fredericton CA: 61–64.

Lock B., Simon A. M., Stubblefield K. & Hargrove L. (2011) Prosthesis-guided training for practical use of pattern recognition control of prostheses. In: Parker P. A. (ed.) MEC'11 Raising the standard. UNB, Fredericton: 61–64.

Lutterer W. (2012) Deutero-learning. In: Seel N. M. (eds.) Encyclopedia of the sciences of learning. Springer, New York: 939–941.

Mathewson K. W. & Pilarski P. M. (2017) Reinforcement learning based embodied agents modelling human users through interaction and multi-sensory perception. In: AAAI spring symposium on interactive multisensory object perception for embodied agents, March 27–29, Stanford University, USA: 477–481.

Merleau-Ponty M. (1962) Phenomenology of perception. Routledge and Kegan Paul, New York.

Metzger A. J., Dromerick A. W., Holley R. J., Lum P. S. (2012) Characterization of compensatory trunk movements during prosthetic upper limb reaching tasks. Archives of Physical Medicine and Rehabilitation 93: 2029–2034.

Micera S., Carpaneto J. & Raspopovic S. (2010) Control of hand prostheses using peripheral information. IEEE Reviews in Biomedical Engineering 3: 48–68.

Neumann J. von (1958) The computer and the brain. Yale University Press, New Haven CT.

Packer M. J & Goicoechea J. (2000) Sociocultural and constructivist theories of learning: Ontology, not just epistemology. Educational Psychologist 35(4): 227–241.

Parker P. A. & Scott R. N. (1985) Myoelectric control of prostheses. Critical Reviews in Biomedical Engineering 13(4): 283–310.

Peerdeman B., Boere D., Witteveen H., in 't Veld R. H., Hermens H., Stramigioli S., Rietman H., Veltink P. & Misra S. (2011) Myoelectric forearm prostheses: State of the art from a user-centered perspective. Journal of Rehabilitation Research and Development 48(6): 719–738.

Ravindra V. & Castellini C. (2014) A comparative analysis of three non-invasive human-machine interfaces for the disabled. Frontiers in Neurorobotics 8: 24.

Samuel A. L. (1959) Some studies in machine learning using the game of checkers. IBM Journal of Research and Development 3(3): 210–229.

Sarkar A. (2016) Constructivist design for interactive machine learning. In: Proceedings of the 2016 CHI conference extended abstracts on human factors in computing systems (CHI EA '16) ACM, New York: 1467–1475.

Scheme E. & Englehart K. (2011) Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use. Journal of Rehabilitation Research and Development 48(6): 643–659.

Schweitzer W., Thali M. J. & Egger D. (2018) Case-study of a user-driven prosthetic arm design: Bionic hand versus customized body-powered technology in a highly demanding work environment. Journal of NeuroEngineering and Rehabilitation 15: 1.

Sensinger J. W., Lock B. A. & Kuiken T. A. (2009) Adaptive pattern recognition of myoelectric signals: Exploration of conceptual framework and practical algorithms. IEEE Transactions on Neural Systems and Rehabilitation Engineering 17(3): 270–278.

Shalev-Shwartz S. & Ben-David S. (2014) Understanding machine learning: From theory to algorithms. Cambridge University Press, New York.

Shaw R. E., Kugler P. N. & Kinsella-Shaw J. (1990) Reciprocities of intentional systems. In: Warren R. & Wertheim A. H. (eds.) Resources for ecological psychology: Perception and control of self-motion. Lawrence Erlbaum Associates, Hillsdale NJ: 579–619.

Simon A. M., Hargrove L. J., Lock B. A. & Kuiken T. A. (2011) Target achievement control test: Evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses. Journal of Rehabilitation Research & Development 48(6): 619–628.

Simon A. M., Lock B. A. & Stubblefield K. A. (2012) Patient training for functional use of pattern recognition-controlled prostheses. Journal of Prosthetics and Orthotics 24(2): 56–64.

Simon A. M., Lock B. A., Stubblefield K. A. & Hargrove L. J. (2011) Prosthesis-guided training increases functional wear time and improves tolerance to malfunctioning inputs of pattern recognition–controlled prostheses. In: MEC 11 Raising the Standard. Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium. University of New Brunswick, Fredericton CA: 65–69.

Strazzulla I., Nowak M., Controzzi M., Cipriani C. & Castellini C. (2017) Online bimanual manipulation using surface electromyography and incremental learning. IEEE Transactions on Neural Systems and Rehabilitation Engineering 25: 227–234.

Taylor D. R. & Finley F. R. (1974) Multiple-axis prosthesis control by muscle synergies. In: Herberts P., Kadefors R., Magnusson R. & Petersen I. (eds.) The control of upper-extremity prostheses and orthoses. C. C. Thomas, Springfield IL: 181–189.

Uellendahl J. & Tyler J. (2016) A case series study of pattern recognition for upper-limb prosthesis control. In: Proceedings of the first international symposium on innovations in amputation surgery and prosthetic technologies, Chicago IL: 68.

Uexküll J. von (2010) A foray into the worlds of animals and humans: With a theory of meaning. Translated by J. D. O'Neil. University of Minnesota Press, University of Minnesota Press, Minneapolis MN.

van Dijk L., van der Sluis C. K., van Dijk H. W. & Bongers R. M. (2016) Task-oriented gaming for transfer to prosthesis use. IEEE Transactions on Neural Systems and Rehabilitation Engineering 24(12): 1384–1394.

Varela F. J., Thompson E. & Rosch E. (1991) The embodied mind: Cognitive science and human experience. MIT Press, Cambridge MA.

Wagstaff K. L. (2012) Machine learning that matters. In: Langford J. & Pineau J. (eds.) Proceedings of the 29th international conference on machine learning (ICML-12) Omnipress, Madison WI: 529–536.

Wang R., King T., Ossipov M. H., Rossomando A. J., Vanderah T. W., Harvey P., Cariani P., Frank E., Sah D. W., Porreca F. (2008) Persistent restoration of sensory function by immediate or delayed systemic artemin after dorsal root injury. Nature Neuroscience 11(4): 488–496.

Yungher D. & Craelius W. (2012) Improving fine motor function after brain injury using gesture recognition biofeedback. Disability and Rehabilitation: Assistive Technology 7(6): 464–468. http: //www.tandfonline.com/doi/full/10.3109/17483107.2011.650782.

Zhou P., Lowery M. M., Englehart K. B., Huang H., Li G., Hargrove L., Dewald J. P. A. & Kuiken T. A. (2007) Decoding a new neural machine interface for control of artificial limbs. Journal of Neurophysiology 98(5): 2974–2982.

Publication 4 Simultaneous Assessment and Training of an Upper-Limb Amputee using Incremental Machine-Learning-based Myocontrol: A Single-Case Experimental Design

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RESEARCH **Open Access**

Simultaneous assessment and training of an upper-limb amputee using incremental machine-learning-based myocontrol: a single-case experimental design

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Abstract

Background Machine-learning-based myocontrol of prosthetic devices suffers from a high rate of abandonment due to dissatisfaction with the training procedure and with the reliability of day-to-day control. Incremental myocontrol is a promising approach as it allows on-demand updating of the system, thus enforcing continuous interaction with the user. Nevertheless, a long-term study assessing the efficacy of incremental myocontrol is still missing, partially due to the lack of an adequate tool to do so. In this work we close this gap and report about a person with upper-limb absence who learned to control a dexterous hand prosthesis using incremental myocontrol through a novel functional assessment protocol called SATMC (Simultaneous Assessment and Training of Myoelectric Control).

Methods The participant was fitted with a custom-made prosthetic setup with a controller based on *Ridge Regression with Random Fourier Features* (RR-RFF), a non-linear, incremental machine learning method, used to build and progressively update the myocontrol system. During a 13-month user study, the participant performed increasingly complex daily-living tasks, requiring fine bimanual coordination and manipulation with a multi-fingered hand prosthesis, in a realistic laboratory setup. The SATMC was used both to compose the tasks and continually assess the participant's progress. Patient satisfaction was measured using Visual Analog Scales.

Results Over the course of the study, the participant progressively improved his performance both objectively, e.g., the time required to complete each task became shorter, and subjectively, meaning that his satisfaction improved. The SATMC actively supported the improvement of the participant by progressively increasing the difficulty of the tasks in a structured way. In combination with the incremental RR-RFF allowing for small adjustments when required, the participant was capable of reliably using four actions of the prosthetic hand to perform all required tasks at the end of the study.

Conclusions Incremental myocontrol enabled an upper-limb amputee to reliably control a dexterous hand prosthesis while providing a subjectively satisfactory experience. The SATMC can be an effective tool to this aim.

Keywords Hand prosthesis, Machine-learning control, Myocontrol, Training, Single-case experimental design

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Background

In our world tailored to interact using one's hands people with upper limb absence use prosthetic limbs to overcome resulting challenges. Upper-limb prostheses have seen major technological advances in the last decade. Multi-articulated prosthetic hands with individual finger actuation are becoming more present and can be combined with (multi-articulated) actuated prosthetic wrists [1].

These technological advancements are accompanied by novel developments in myocontrol, which is the control of (prosthetic) devices using muscle signals, most commonly based on electromyography (EMG). These developments are manifold and include the distinction of up to 11 intended *actions*, such as *power grasp*, *pointing index* or *wrist flexion*, with a success rate above 94% [2], the usage of high-density sensor matrices for control of up to 4 degrees of freedom (DOFs) of a robotic arm [3] or for decoding spike trains [4, 5], feature extraction based on deep learning [6] or the usage of different sensor modalities, such as forcemyography [7–10], ultrasound [11, 12] or electrical impedance tomography [13, 14]. Yet, the clinical standard since decades is a two-electrode control that uses a EMG-based switching command to cycle through the DOFs of the prosthetic setup [15]. Although many approaches, such as the ones mentioned in this paragraph, provide promising results, only few that are based on machine learning (ML) have reached the users [16, 17].

The process from initial algorithm development to applying the algorithm in daily living prosthesis use faces a number of challenges. An early involvement of the user is essential, since findings offline (without the user in the loop) do not translate to the online application (with the user in the loop) [18]. Hence, online testing with the user performing goal-reaching tasks has become the standard in evaluating the performance of a novel method [8, 19–22]. Moreover, the introduction of ML-based methods adds a further processing step to myocontrol. Instead of directly using sensor readings as control for prostheses, these signals are first processed and interpreted before they can be converted into control signals of the hand. This introduces a further layer of complexity for the user. Although measures have been taken to make this layer as intuitive and easy-to-use as possible [23, 24], studies have shown that ML-based methods require an extended training and learning phase [25, 26], which users can experience as exhaustive, potentially leading to abandonment [27–29]. A further aspect that is challenging for ML-based myocontrollers is the *limb-position effect* [30, 31]. It describes the issue that the measured EMG depends on the specific body posture, potentially leading to the myocontroller detecting another action then intended. Particularly ML-based myocontrollers suffer from this effect as already minor changes in the muscle configuration can have a significant influence on the recognition of an action [31].

Incrementality can be a solution to deal with these issues. Incremental ML methods allow the user to update or add new information to the training data, instead of retraining completely anew. This reduces calibration time significantly. Small and/or regular updates to an ML-based myocontroller in positions where it is required have been shown to improve performance of a myocontroller [25, 32–34].

However, existing validated assessment tools don't explicitly take incrementality into account and are not tailored for use with ML-based myocontrollers. A recent overview has been provided by Kyberd [35].

We have taken inspiration from a number of validated assessment tools and developed the *Simultaneous Assessment and Training of Myoelectric Control* (SATMC) procedure. It can deal with incrementality and the specifics of novel myocontrol methods, allows the user to gradually improve and at the same time continuously assesses the myocontrol system. We have published a preliminary description and evaluation previously [36].

In this work we performed a long-term study involving one transradial amputee fitted with a multi-articulated prosthetic hand and a custom-built socket controlled by an incremental myocontroller based on *Ridge Regression with Random Fourier Features* (RR-RFF) [7, 8, 25, 32, 33]. Using the SATMC procedure allowed the participant to train how to use the incremental myocontroller, while simultaneously assessing the performance of the user in daily-living tasks. The goal of this study was to show that an incremental training protocol can be used to train a user to learn a complex myocontroller while at the same time assess the improvement of the user.

Methods

User study

After being thoroughly informed about the content and risks of the study, the participant (P) signed an informed consent form and agreed to participate. This study was formally approved by the host institution's internal committee for data protection (ASDA 14/05 TOP 6.5 on 02.09.2014) and it followed the guidelines of the World Medical Association's declaration of Helsinki. The male participant was 35 years old at the start of the study. He had undergone a traumatic transradial amputation of his left arm 11 years prior to the study. He routinely used a Variplus hand (Otto Bock GmbH) with a standard two-sensor control for opening and closing of the hand. He had neither experience with multi-articulated prosthetic hands nor with ML-based myocontrol. For the

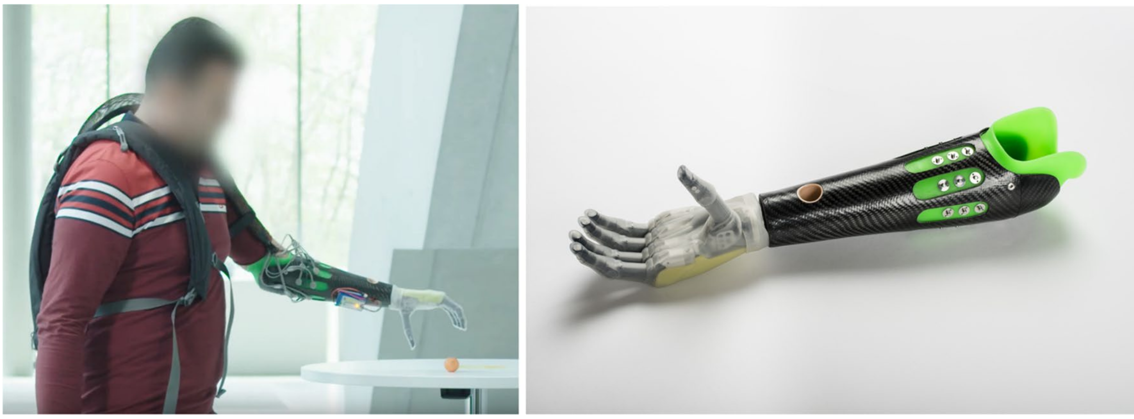


Fig. 1 Prosthetic setup in our study; On the left: Participant P wearing custom-build hardware consisting of a small backpack housing hardware for data acquisition and wireless communication and a battery. On the right: Custom-build socket with eight snap-on electrodes uniformly distributed around the circumference of the stump. The prosthetic hand was the i-LIMB Revolution (Össur hf)

participation he received financial compensation for the cost of the commute and his time.

During the experiment two experimenters were present at all times. One person was the operator, who was concerned with supervising the myocontrol including updates, monitoring of the signals and assuring the correct completion of the protocol. A second person had a purely observational role making notes regarding the behaviour and manner of task execution.

The user study is based on *Single-Case Experimental Design* (SCED) [37–39], which provides guidelines for performing structured experiments involving only a small number of participants. Although less common in the field of prosthetics, a number of studies following these guidelines have been performed [40–43]. SCED-based studies can provide a high level of evidence, if carried out correctly [38].

Prosthetic hardware

For the purpose of this study P was fitted with a custom-made prosthetic socket that could house eight myoelectric sensors. The design and the fitting were done by a certified prosthetist of Pohlig GmbH in Traunstein, Bavaria, Germany (part of Otto Bock GmbH). For the setup in this study eight 13E200=50 MyoBock sensors were used [44]. This is a larger number than the two-sensor arrangement of direct control, but eight sensors have already been successfully used in daily living as part of commercially available solutions [16, 17]. The electrodes were placed uniformly distributed around the circumference of the proximal forearm using snap-on domes. The most proximal snap-ons were placed 6*cm* from the medial epicondyle. The inter-dome distance spans 1.5*cm*. With this arrangement the electrodes cover the majority of the forearm muscles. These were embedded in the inner silicone layer of the design, while the outer layer was manufactured out of carbon fibre, see Fig. 1. Using custom-made electronics, the sensors were connected to the aforementioned snap-on domes. The communication between the sensors and the desktop computer used for computation was wired in the beginning of the experiment and wireless from session 24 onwards. The hardware was not optimised to fit in the confined space of the prosthetic socket. Hence, P was required to carry a small backpack with battery-powered electronics for reading the sensors and transmitting these readings to the desktop machine (Fig. 1, left-hand side). There was no additional weight on the prosthesis impacting the performance besides the socket and the prosthetic hand, which was an i-LIMB Revolution (Össur hf). The i-LIMB Revolution is capable of individual finger flexion for all five fingers and additionally thumb abduction.

Incremental myocontrol algorithm

The basis of RR-RFF is *Ridge Regression*, which is linear regression with a regularisation parameter,

$$\hat{\boldsymbol{y}} = \boldsymbol{W}\boldsymbol{x} \quad \text{with} \quad \boldsymbol{W} = (\boldsymbol{X}^T\boldsymbol{X} + \lambda\boldsymbol{I})^{-1}\boldsymbol{X}^T\boldsymbol{Y}. \tag{1}$$

The terms in Eq. (1) represent the predicted values $\hat{\boldsymbol{y}}$, the regression weights $\boldsymbol{W}$, the input $\boldsymbol{x}$, as well as the regularisation hyperparameter λ and the identity matrix $\boldsymbol{I}$. $\boldsymbol{X}$ and $\boldsymbol{Y}$ are the collection of all data used for training and the associated target values, respectively.

RR-RFF is an extension of *Ridge Regression*, where the input $\boldsymbol{x}$ is projected into a higher-dimensional space using a finite-dimensional approximation of a *Gaussian Kernel*,

$$\boldsymbol{\phi} = \phi(\boldsymbol{x}) = \sqrt{2}\cos(\boldsymbol{\Omega}\boldsymbol{x} + \boldsymbol{\beta}), \tag{2}$$

$$\boldsymbol{\Phi} = \phi(\boldsymbol{X}) = \sqrt{2/D}\cos(\boldsymbol{X}\boldsymbol{\Omega}^T + \mathrm{B}), \tag{3}$$

with

$$\boldsymbol{\Omega} \sim \mathcal{N}(0, \sigma^2), \tag{4}$$

$$\boldsymbol{\beta}, \mathrm{B} \sim \mathcal{U}(-\pi, \pi), \tag{5}$$

where σ^2 is a hyperparameter and represents the variance of the Gaussian Kernel. This mapping $\phi : \mathbb{R}^d \rightarrow \mathbb{R}^D$ transforms the d-dimensional input space into a D-dimensional feature space. D is a further hyperparameter of the algorithm. Applying this transformation to Eq. (1) results in the final expression of RR-RFF,

$$\hat{\boldsymbol{y}} = \boldsymbol{W}\boldsymbol{\phi} \text{with} \quad \boldsymbol{W} = (\boldsymbol{\Phi}^T\boldsymbol{\Phi} + \lambda\boldsymbol{I})^{-1}\boldsymbol{\Phi}^T\boldsymbol{Y}. \tag{6}$$

This non-linear mapping allows the algorithm to adequately fit data, where a linear mapping would not be sufficient. A detailed description of the underlying properties will not be covered here as previous publications already have done so [32, 45, 46].

An arbitrary number of electrodes can serve as input to the algorithm. The eight sensors used in this study are non-invasive and provide an already pre-filtered surface EMG (sEMG) signal, which is amplified, bandpass-filtered, and rectified onboard [44]. This signal was sampled at 100 Hz and further low-pass filtered with a 1$^{\text{st}}$ order Butterworth filter with a cut-off frequency of 1 Hz. The resulting feature was the envelope of the sEMG signal and comprised the input to the RR-RFF-based myocontroller. The predicted output $\hat{\boldsymbol{y}}$ of Eq. (6) was the individual DOFs of the prosthetic hand. These were the flexion of each of the five fingers plus the abduction of the thumb. By controlling each finger different actions can be composed, e.g. *power grasp*.

Furthermore, a number of features of RR-RFF were relevant in the context of this user study. First, based on previous studies, hyperparameters and modifications have been identified that allow for a fast and incremental update of the algorithm [32]. This feature is particularly relevant when dealing with the *limb position effect*. Due to incremental learning in positions, where the control becomes unstable, additional repetitions can be gathered, the algorithm can be updated and the execution can continue after a few seconds. Furthermore, the RR-RFF-based myocontroller predicts the individual DOFs of the prosthetic hand, e.g. *index flexion*, instead of action as a whole, e.g. *power grasp*. This feature allowed us to use incrementality for action training. That is, a new action that is added to an existing action set is represented by an additional configuration of the individual DOFs of the prosthetic limb and therefore does not require a further DOF in the vector of the target values $\hat{y}$. This feature allows the user to start with a minimal functional training and perform updates only when required and, therefore, reduces the initial calibration time of the myocontroller. An initial training can consist of only *rest* and *power grasp* and in a later update additional actions can be added, e.g. *precision grasp*.

Second, collection of training data is only done on the sustained part of action execution. This is the static part of the feature-data, when the user maintains an action with an approximately constant force. Often ramped training data is collected for regression-based algorithms [47–49]. This refers to the onset (and offset) of the feature-data, when transitioning from resting to an action. While there are benefits of using the dynamic part of the contraction [31], some users are not capable to follow a ramped signal closely [32, 50]. To avoid poorly labelled data, only the sustained part of an action is taken into account, which can be maintained for a few seconds. This has the added benefit that a screen displaying the visual stimulus is not required simplifying updates in positions and during tasks, where no screen is visible.

Third, the myocontroller is capable of *progressive forgetting*. Under the assumption that updates are required once a given situation has changed and/or the participant expresses different/improved sEMG signals, older training data becomes obsolete. The behaviour is that of a ring buffer, where the addition of an entry beyond the size of the buffer leads to the removal of the first/oldest entry. Since the training of the myocontrol is based on repetitions of actions, the size was set to five repetitions per action. This means that up to the fifth repetition the repetitions are added to the training data and therefore increasing the amount of training data. With the addition of the sixth repetition the chronologically first repetition will be removed. Therefore, after adding the fifth repetition to the training data the amount of data remains constant. This process applies to each action trained.

Simultaneous assessment and training of myoelectric control (SATMC)

Based on the issues described in "Background" we formulated four aspects (A1–A4) that we deem important in the design of an assessment and training tool for ML-based myocontrol: *repeatability and increasing difficulty* (A1), *postural variation during tasks* (A2), *multiple actions per task* (A3), and *a short familiarisation time for the rater* (A4).

Among validated assessment tools none satisfies all four of these aspects. Exemplary from the most common tests for prosthetic control we evaluate the *Assessment of Capacity for Myoelectric Control* (ACMC) [51], the *Southampton Hand Assessment Procedure* (SHAP) [52], and the *Clothespin Relocation Test* (CRT) [53] considering the aspects A1–A4.

The ACMC is an observational assessment tool for prosthetic usage that can be performed in the home of a user or a room specifically designed to provide a household environment. Being able to observe a user in an environment as close as possible to daily living provides highly relevant insights in the validity of a given prosthetic system. As the tasks can be any activity of daily-living aspects A2 and A3 can easily be fulfilled. However, no specific guidelines provide structure to task repetition or increase of task difficulty (A1). Furthermore, professional training is required to draw proper conclusions purely from observations, making the ACMC less accessible (A4). Its current version is not tailored to multi-articulated prostheses [35].

The SHAP on the other hand is a test that can be administered with minimal training of the experimenter (A4) and only requires a suitcase of objects for its execution. The SHAP is a collection of tasks that are abstractions of activities of daily living (ADLs). They are performed in a seated position at a table and evaluated using an easy-to-use measure, the time to finish a task. The seated position only allows for limited assessment of issues arising from the limb position effect and therefore does not fulfil A2. The tasks have different levels of difficulty, however the limited options to vary tasks do not allow for a structured approach to increase difficulty (A1). Furthermore, the SHAP is comprised of unilateral tasks, which are all based on grasping actions (A3).

A good example of a test targeted at multi-articulated prostheses and complex tasks is the CRT. This test requires simultaneous activation of a prosthetic wrist and hand and thereby satisfies A3. As the name suggests clothespins need to be relocated from a horizontal bar to a vertical one, which in this case requires a rotation of the clothespins while maintaining a firm grip. Since the CRT consists of one task only, it offers rather little variability in its execution and difficulty (A1), but it contains postural variation (A2). Furthermore, only once a user is proficient in the use of their prosthesis the CRT can offer insight in the user's capabilities. As no dedicated training of the experimenter is required A4 is satisfied.

The SATMC combines the advantages of the aforementioned assessment tools with added focus on aspects A1–A4. The following paragraphs describe how these aspects are implemented in the SATMC. They describe the *guidelines*, the implementation of structured *tasks* and a customised *experimental setup*.

Guidelines

An essential feature of the SATMC is a progressive increase in difficulty at a speed adaptable to the capabilities of the user (A1). This increase is two-fold. On the one hand each task has different levels of difficulty and on the other hand within the protocol we employ a stepwise increase in control complexity. The latter is realised by increasing the number of actions to control. In the beginning only two actions are available to the user. Starting with an action very commonly used, e.g. a hand close gesture/power grasp and a hand open / rest gesture. This initial action set already provides the functionality of common gripper prostheses.

The SATMC is organised in *sessions* and *phases*. A *session* is a collection of tasks administered as a closed unit. Per visit only one session is performed. A *phase* is characterised by multiple sessions with a specific action set and therefore spans multiple visits of the participant. Moving from one phase to another represents an increase in controller complexity as another action is added to the current action set.

In a session the user performs three repetitions of a set of five tasks. Each task has five variations of increasing difficulty, which are designed to fulfil aspects A2 and A3. Further details regarding tasks can be found in Paragraph "Tasks". After a set of five tasks, the user is asked to self-evaluate their performance. For this purpose, we use a *visual analogue scale* (VAS), on which better or easier performance is rated higher. These self-evaluations determine the degree of difficulty for the next task variations. Based on an equal split of the scale, an evaluation of VAS 0–3.3 results in a repetition of the previous level of difficulty, while an evaluation of VAS 3.4–6.6 leads to an increase by one step and an evaluation of VAS 6.7–10 leads to an increase by two steps. These evaluations determine the next five variants of the tasks. Following their execution, this second set of task variants is evaluated determining the third and last five variants of the tasks. They are performed and evaluated, which then concludes one session with a total of 15 task executions. It is possible that in case of low VAS ratings a variant of a task is repeated three times within one session. Once a user becomes proficient in the performance with a given set of actions, a new phase of the study can be started. Two consecutive sessions, in which the self-assessment of all 15 tasks is in the range VAS 6.6–10 determines this point and a new action can be added to the existing set. Since the set of actions has been expanded the tasks have to be updated as well to ensure the usage of all available actions. An exemplary graphical representation of this process is given in Fig. 2.

Additionally to the self-assessment by the user, an easy-to-use measure has been chosen to assess the tasks in order to only require little to no training of the experimenter (A4). For this purpose, the *task completion time* (TCT) was selected. It has been shown that timing tasks is a key parameter for prosthetic use [54]. It is important to note that a focus was put on continuing a task rather

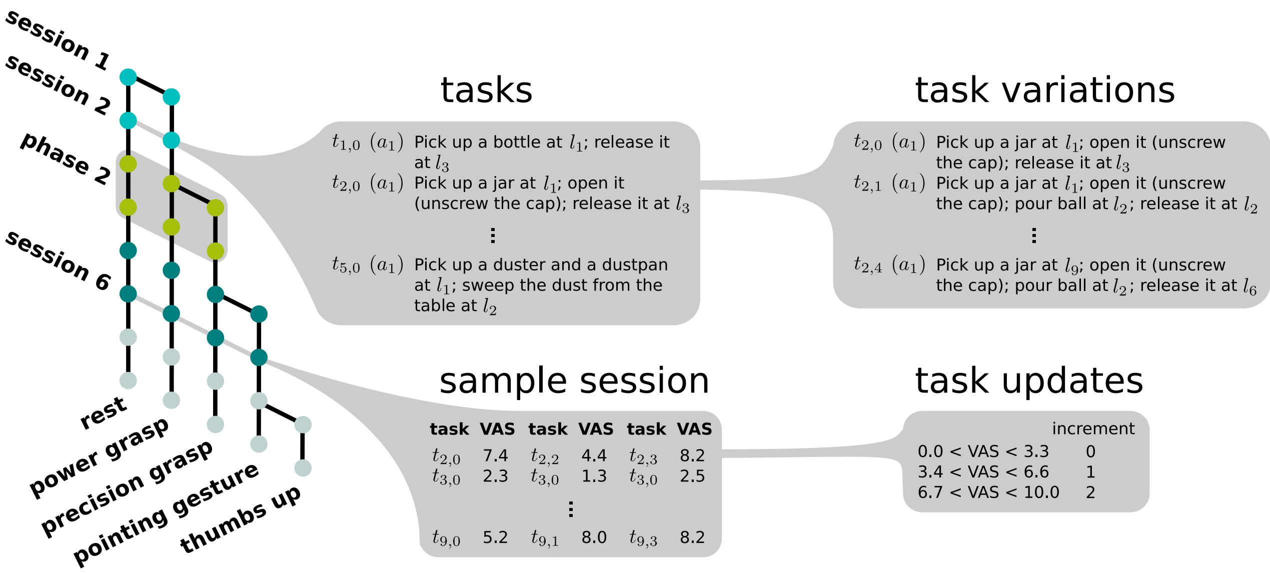


Fig. 2 Diagram of the SATMC: Each bifurcation indicates the onset of a new phase, where an action is added to the existing ones and the tasks are updated. Sessions are visualised by rows spanning a set of actions of the same colour. Balloons *tasks* and *task variations* list exemplary tasks with exemplary task variations for a given session. Furthermore, balloon *sample session* gives a short overview of the process in an example session, where the tasks in the first column are executed, evaluated in column two and updated accordingly. The update is based on the VAS evaluation, see balloon *task updates*. This process is then repeated until 15 tasks have been performed and evaluated. $t_{i,j}$ represent variation j of task i. a_k is action k and l_m is landmark m in the study setup

than ending it prematurely due to erroneous behaviour. In case an object e.g. is dropped, rather than ending a task and counting this task as failed the user is encouraged to pick the object up again and continue with the task. This becomes particularly relevant in situations where the control algorithm reaches its limits, e.g. postures in which no training was performed. In these situations, where an execution is not possible due to poor performance of the myocontroller and retraining is required, the additional time spent on retraining is part of the task execution time and contributes to the overall evaluation. Therefore, algorithms that allow for a quick recalibration or even incremental learning will have shorter task durations in difficult situations.

Moreover, in order to reduce the burden on the user, they should be informed that the tasks are being timed, but they are not required to perform the tasks as fast as possible. The ADL-like tasks are not of a competitive nature. A fundamental principle in SATMC is repetition and improvement over time. The latter should still be evident in case the tasks are not executed as quickly as possible.

As it was mentioned in "User study" the SATMC follows SCED. Two central aspects are *direct replication* and the introduction of a *baseline*. The different phases of the SATMC correspond to *direct replication*, where each phase is a different condition the ML-based myocontroller is assessed in. To ensure a *baseline* throughout the administration of the SATMC one of the five tasks should be kept unchanged.

Following these guidelines, users can train their capabilities and the experimenter can assess the performance of user, prosthesis and myocontrol algorithm. The end of an experimental study can either be reached once this performance reaches its limits or by personal preference of the participant.

Tasks

Task design is influenced by aspects A1–A3 defined in "Simultaneous assessment and training of myoelectric control (SATMC)". They mutual influence one another, as changes in posture (A2) and changes in the number of actions per task (A3) impact the difficulty of a task (A1). Height and rotational distance play an important role for grasp stability, i.e. at what height an object needs to be manipulated or over what height difference an object needs to be moved, and the extent of rotation required at the wrist. Furthermore, larger planar distances require for longer periods of stable grasping, which in turn make a task more difficult. These three distance measures (planar, vertical and angular) have been quantified as null, short, middle and long in order to compare different levels of task difficulty. Additionally, introducing subtasks in a given task is a further option to increase difficulty.

We have developed five variations for each task to reflect increasing levels of difficulty. These variations are indicated in the task number, e.g. $t_{2,3}$, which represents the third variation of task number 2. A list of tasks that we have developed according to the aforementioned considerations can be found in Table 1. The values of the three different distance measures per task variation can also be found in Table 1. This list of tasks is not exhaustive and not all tasks are required for the execution of the SATMC. Further tasks can be added keeping the aforementioned criteria in mind. In Table 1 tasks 10–12 have been omitted, since they were not used in the present user study. The tasks for each phase are selected by the person administering the SATMC. The set of five tasks should require all actions that have been trained so far, but not more, and should not be changed during a phase.

In the task descriptions in Table 1 several abbreviations are used. The landmarks l_n can be found in the next paragraph describing the setup. The actions that are involved in each task are abbreviated by a_n and correspond to

(a_1) power grasp,
(a_2) precision grasp,
(a_3) pointing gesture,
(a_4) preshaping for flat grasp (thumbs up), and
(a_5) flat grasp.

Setup

An overview of an instance of a setup with landmarks l_n indicated as numbers n can be found in Fig. 3. These landmarks can be described as follows:

(l_1) on the rectangular table, straight in front of the participant
(l_2) on the rectangular table, half a meter laterally towards the intact hand.
(l_3) on the corner of the rectangular table.
(l_4) on the round table.
(l_5) on the ground, one side of the round table.
(l_6) on the ground, other side of the round table (wastebasket).
(l_7) on the shelf, lower level ($\sim$ 0.20 m above the ground).
(l_8) on the shelf, middle level ($\sim$ 1.00 m above the ground).
(l_9) on the shelf, top level ($\sim$ 1.80 m above the ground).

The participant is seated in front of l_1 at the beginning of a task. Based on these landmarks we approximated the difficulty in terms of planar and vertical distance, see Table 1. For example, picking up an object at l_1 and releasing it at l_2 is easier than picking it up at l_1 and bringing it to l_9.

Each task requires some objects to manipulate or move around. A set of objects required for the tasks in Table 1 can be found in Fig. 4.

Analysis

Additionally to the primary measures TCT and VAS, we recorded sEMG-data for the entire duration of the experiment and logged each algorithm update with sEMG-data and timing for further evaluation.

Training data can be evaluated using common measures of data properties, e.g. the Separability Index (SI) and the Repeatability Index (RI) [21, 55, 56]. SI is a measure of cluster separation, where the distance between cluster centroids is weighted with the spread of the clusters.

$$\mathrm{SI} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{2}\sqrt{(\mu_i - \mu_{ci})^T S^{-1}(\mu_i - \mu_{ci})}\right), \qquad (7)$$

with n representing the number of actions, μ_i the centroid of action i, μ_{ci} the centroid of the most conflicting action for action i and $S = \frac{S_i + S_{ci}}{2}$ with S_i and S_{ci} representing the covariance of the aforementioned two corresponding actions.

RI usually compares the feature-data collected during training with the feature-data from the testing phase. Since the execution of the tasks in the SATMC is rather free, there is no ground truth in the testing phase that can be used for this comparison. As an alternative, we compare the repetitions of an action that are used to train the myocontrol, which in turn provides information on the data consistency between repetitions. The RI is a measure of difference between these repetitions per action, i.e. a distance measure of the repetition centroid weighted with the spread of the repetitions.

$$\mathrm{RI} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{\binom{r_i}{2}}\sum_{\substack{j=1\\k=1\\j\neq k}}^{r_i}\left(\frac{1}{2}\sqrt{\left(\mu_{i,j} - \mu_{i,k}\right)^T S^{-1}\left(\mu_{i,j} - \mu_{i,k}\right)}\right), \qquad (8)$$

with n representing the number of actions, r_i the number of repetitions for action i, $\mu_{i,j/k}$ the centroid of repetitions j/k of action i, and $S = \frac{S_{i,j} + S_{i,k}}{2}$ with $S_{i,j}$ and $S_{i,k}$ representing the covariance of two different repetitions of action i. The measures SI and RI were calculated only using training data.

Throughout the study sEMG-data was gathered during task execution together with the parameters and hyperparameters of the RR-RFF-based algorithm. Since

Table 1 Description of tasks

Task #	Action(s) Involved	Distance Planar	Vertical	Angular	Description
$t_{1,0}$	(a_1)	Short	Null	Null	Pick up a bottle at l_1; release it at l_3.
$t_{1,1}$	(a_1)	Middle	Short	Null	Pick up a bottle at l_1; release it at l_4.
$t_{1,2}$	(a_1)	Long	Middle	Null	Pick up a bottle at l_1; release it at l_9.
$t_{1,3}$	(a_1)	Short	Null	Middle	Pick up a bottle at l_1; pour water from it in a mug at l_2; release it at l_1.
$t_{1,4}$	(a_1)	Middle	Middle	Middle	Pick up a bottle at l_9; pour water from it in a mug at l_4; release it at l_9.
$t_{2,0}$	(a_1)	Short	Null	Null	Pick up a jar at l_1; open it (unscrew the cap); release it at l_3.
$t_{2,1}$	(a_1)	Short	Null	Middle	Pick up a jar at l_1; open it; pour ball at l_2; release it at l_2.
$t_{2,2}$	(a_1)	Middle	Middle	Middle	Pick up a jar at l_1; open it; pour ball at l_2; release it at l_6.
$t_{2,3}$	(a_1)	Long	Middle	Middle	Pick up a jar at l_8; open it; pour ball at l_2; release it at l_6.
$t_{2,4}$	(a_1)	Long	Long	Middle	Pick up a jar at l_9; open it; pour ball at l_2; release it at l_6.
$t_{3,0}$	(a_1)	Short	Null	Null	Pick up a basket at l_1; release it at l_3.
$t_{3,1}$	(a_1)	Middle	Null	Null	Pick up a basket at l_1; release it at l_4.
$t_{3,2}$	(a_1)	Middle	Middle	Null	Pick up a basket at l_5; release it at l_4.
$t_{3,3}$	(a_1)	Middle	Middle	Null	Pick up a basket at l_5; release it at l_2; take out object to l_1.
$t_{3,4}$	(a_1)	Middle	Long	Null	Pick up a basket at l_5; release it at l_2; take out object to l_9
$t_{4,0}$	(a_1)	Short	Null	Null	Pick up salami at l_1; bring it to chopping board at l_2; slice it with knife.
$t_{4,1}$	(a_1)	Middle	Null	Null	Pick up salami at l_3; bring it to chopping board at l_2; slice it with knife.
$t_{4,2}$	(a_1)	Middle	Null	Null	Pick up salami at l_4; bring it to chopping board at l_2; slice it with knife.
$t_{4,3}$	(a_1)	Long	Middle	Null	Pick up salami at l_9; bring it to chopping board at l_2; slice it with knife.
$t_{4,4}$	(a_1)	Long	Middle	Null	Pick up cutting board at l_8; bring it to l_2; pick up salami at l_9; bring it to chopping board at l_2; slice it with knife.
$t_{5,0}$	(a_1)	Short	Null	Null	Pick up duster and dustpan at l_1; sweep the dust from the table at l_2.
$t_{5,1}$	(a_1)	Middle	Null	Null	Pick up duster and dustpan at l_1; sweep the dust from the table at l_4.
$t_{5,2}$	(a_1)	Long	Null	Null	Pick up duster and dustpan at l_1; sweep the dust from the table at l_4; chuck the dust out in a waste-basket at l_6.
$t_{5,3}$	(a_1)	Long	Middle	Null	Pick up duster and dustpan at l_7; sweep the dust from the table at l_4; chuck the dust out in a waste-basket at l_6.
$t_{5,4}$	(a_1)	Long	Middle	Null	Pick up duster and dustpan at l_7; sweep dust from the table at l_4; chuck dust in wastebasket at l_6; bring duster and dustpan back at l_7.
$t_{6,0}$	(a_2)	Short	Null	Null	Pick up DLR cube at l_1; stack it on another DLR cube at l_2.
$t_{6,1}$	(a_2)	Middle	Null	Null	Pick up DLR cube at l_1; stack it on another DLR cube at l_4.
$t_{6,2}$	(a_2)	Long	Long	Null	Pick up DLR cube at l_7; another at l_9; stack it on another DLR cube at l_2.
$t_{6,3}$	(a_2)	Middle	Null	Null	Pick up a checker at l_1; stack it on another checker at l_4.
$t_{6,4}$	(a_2)	Long	Long	Null	Pick up a checker at l_7; another at l_9; stack it on another checker at l_2.
$t_{7,0}$	(a_2)	Null	Null	Null	Fold towel at l_2.
$t_{7,1}$	(a_2, a_1)	Short	Null	Null	Get towel at l_3; Fold towel at l_2.
$t_{7,2}$	(a_2, a_1)	Middle	Middle	Null	Get towel at l_3; Fold towel at l_2; return to l_9.
$t_{7,3}$	(a_2, a_1)	Middle	Long	Null	Get towel at l_4; Fold towel at l_2; return to l_9.
$t_{7,4}$	*NA*				
$t_{8,0}$	(a_2)	Null	Null	Null	Pull the handle up to zip the jacket at l_2.
$t_{8,1}$	(a_2)	Middle	Null	Null	Get jacket from l_8; place it at l_1; Pull the handle up to zip the jacket at l_1.
$t_{8,2}$	(a_2)	Null	Null	Null	Wear a jacket with a zipper; pick up the zipper's handle; pull the handle up to zip the jacket.
$t_{8,3}$	(a_2)	Middle	Null	Null	Pick up jacket at l_1; Put jacket on; pick up the zipper's handle; pull the handle up to zip the jacket.
$t_{8,4}$	(a_2)	Middle	Null	Null	Unzip jacket at l_1; Pick up jacket at l_1; Put jacket on; pick up the zipper's handle; pull the handle up to zip the jacket.
$t_{9,0}$	(a_3)	Middle	Short	Null	Turn on the lights.
$t_{9,1}$	(a_3, a_1)	Long	Middle	Short	Turn on the lights, grasp jar at l_9, put it back at l_2, turn the light off.
$t_{9,2}$	(a_3)	Null	Null	Null	Dial a number at l_1 (vertical key).
$t_{9,3}$	(a_3)	Short	Null	Middle	Dial a number at l_1 (horizontal key).

Table 1 (continued)

Task #	Action(s) Involved	Distance Planar	Vertical	Angular	Description
$t_{9,4}$	(a_3, a_1)	Short	Null	Middle	Dial a number at l_1 (horizontal key); pick up handle; put it back down.
⋮	⋮	⋮	⋮	⋮	⋮
$t_{13,0}$	(a_3)	Short	Null	Null	Roll small ball from l_1 to l_2.
$t_{13,1}$	(a_3, a_1)	Middle	Null	Null	Roll small ball from l_3 to l_2, grasp it and put it at l_8.
$t_{13,2}$	(a_3, a_1)	Short	Middle	Null	Roll small ball from l_9 towards you, let it fall, grasp it with the intact hand
$t_{13,3}$	(a_3, a_1)	Middle	Middle	Null	Roll small ball from l_5 towards you, grasp it and put it in wastebasket at l_6
$t_{13,4}$	*NA*				

a_n correspond to actions: (a_1) power grasp, (a_2) precision grasp, (a_3) pointing gesture, (a_4) preshaping for flat grasp (thumbs up), and (a_5) flat grasp; l_n corresponds to landmarks described in Sect. "Setup" and can be seen in Fig. 3. Distance cut-offs are based on the setup and DOF usage. planar: short—only on rectangular table, middle—between rectangular table and round table or between shelf and round table, long—beyond that; vertical: short—between rectangular table and round table, middle – involving one level on the shelf, long—involving two levels on the shelf; angular: short— involving some rotation at the wrist level, middle – involving up to 90° rotation at the wrist level (supination or pronation), long—involving up to 90° rotation at the wrist level (supination and pronation). Note that tasks 10–12 are not presented since they were not used in this study

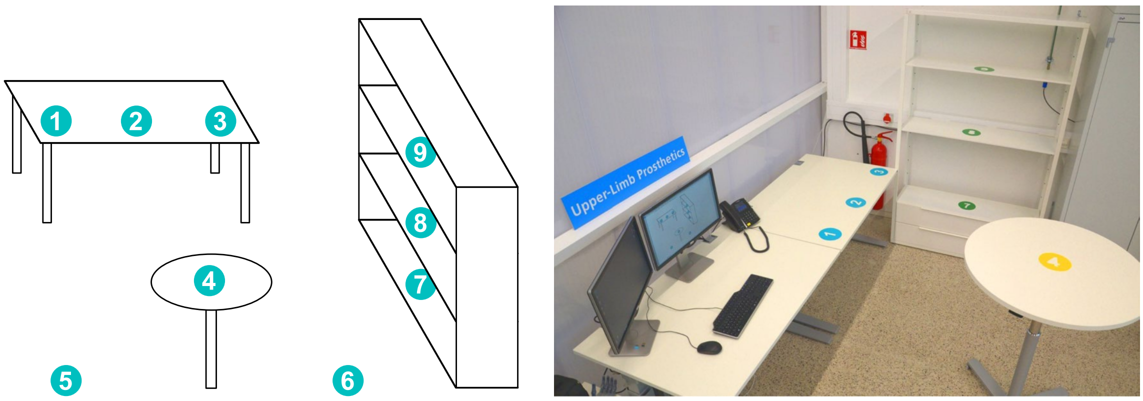


Fig. 3 Overview of the setup used in the SATMC; a sketch on the left and the implementation in our laboratory on the right. Numbers in the setup indicate landmarks l_n, which are used in task descriptions

Fig. 4 Objects used in the user study; from left to right: duster and dust pan, phone, basket, bowl with knife, bottle with "fluid", jar with ball, shirt to fold, mug, and Jenga tower

the myocontroller is based on *Ridge Regression*, the least-squares formulation in Eq. (1) can be interpreted from a Bayesian perspective [57, 58]. Based on a new sample of data $\boldsymbol{x}_{n+1}$, we can not only predict a single value $\hat{\boldsymbol{y}}_{n+1}$, but also get information about the uncertainty of the predicted value. For this purpose, the *predictive distribution* is required

$$f(\hat{\boldsymbol{y}}_{n+1}|\boldsymbol{x}_{n+1}, data), \tag{9}$$

with *data* representing all samples x_i and labels y_i used for the calculation of the ML model. For *Ridge Regression* a closed form for the predictive distribution can be found. It follows a normal distribution with mean μ_{n+1} and variance σ^2_{n+1}

$$f(\hat{\boldsymbol{y}}_{n+1}|\boldsymbol{x}_{n+1}, data) \sim \mathcal{N}(\mu_{n+1}, \sigma^2_{n+1}), \tag{10}$$

with

$$\mu_{n+1} = \left(\boldsymbol{X}^T\boldsymbol{X} + \frac{b}{a}\boldsymbol{I}\right)^{-1}\boldsymbol{X}^T\boldsymbol{Y}\boldsymbol{x}_{n+1}, \tag{11}$$

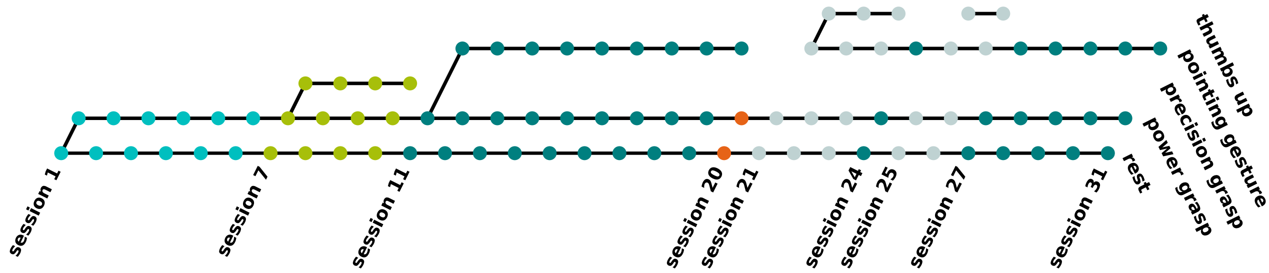


Fig. 5 Overview of all sessions and phases present in the user study. Colours indicate different phases. In session 20, highlighted in orange, P performed tasks from the SATMC with his own prosthesis using direct two-electrode control

$$\sigma^2_{n+1} = \frac{1}{a} + \boldsymbol{x}^T_{n+1}(a\boldsymbol{X}^T\boldsymbol{X} + b\boldsymbol{I})^{-1}\boldsymbol{x}_{n+1}. \tag{12}$$

For a full derivation of μ_{n+1} and σ^2_{n+1} we refer the interested reader to Bolstad and Curran [57].

From Eq. (11) we can see that the mean is equal to the predicted value from Eq. (1). The variance σ^2_{n+1} allows us to evaluate the uncertainty of a predicted value, where high values represent high uncertainty and low values low uncertainty. Therefore, we can assess given the *data*, whether an action has been predicted with a high or a low confidence.

Results

Our participant was followed for 13 months, during which P performed 31 sessions. The sessions took place once per week or every two weeks and lasted between 30 min and 2 h. A longer gap of three months occurred between sessions 22 and 23. Over these 31 sessions we attempted four different phases (characterised by an increase in number of actions), of which one was unsuccessful (*precision grasp*). As a baseline a task was needed that was not too complex but useful and it needed to fit the possibilities provided after initial action training. To this end, we selected task $t_{2,0}$ from Table 1 as a baseline measure. Furthermore, in order to compare the incremental ML-based myocontrol to the standard two-sensor myocontrol a second baseline measure was introduced. This was a single session (session 20) where P used his own prosthesis, which is controlled in this manner.

As a further note, at the beginning of each new session the ML model from the previous session was reloaded. The training data was only updated, when it was required and either asked for by the participant or initiated by the experimenters. This is based on our idea of incrementality, where only minimal initial ML training is performed and changes or uncertainties are dealt with by deliberate updates.

Protocol overview

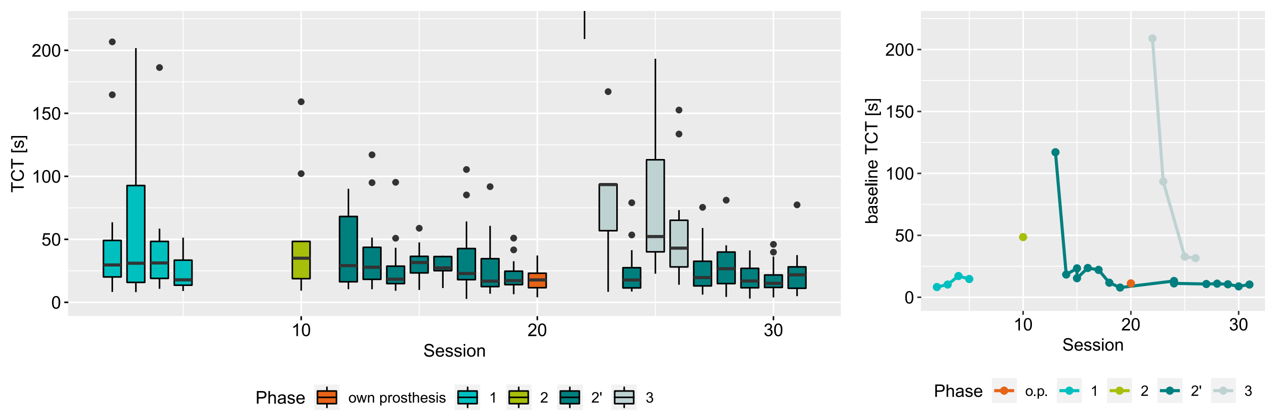
Figure 5 shows the process of the SATMC indicating each session and all actions that were attempted during the different phases. In session 7 the *precision grasp* was introduced, while from session 11 onwards said action was no longer part of the action set. P encountered difficulties with distinguishing the *power grasp* and *precision grasp* reliably. This became evident to the experimenters in terms of heavy jitter and instability in the myocontrol. Therefore, it was decided to consider this phase (phase 2) failed and P switched to a different grasp that was considered to be more likely to create a distinguishable action set, i.e. *pointing index* (phase 2').

After reaching the end of phase 2' P performed the second baseline in session 20 by using his own prosthesis, a myoelectric gripper. The tasks performed therein, were the ones from phase 2'. This session is highlighted in orange.

Timing evaluation

TCT was measured from the beginning of a task to its end, including potential missteps and / or updates to the controller. A summary of the TCT across the full user study can be found in Fig. 6. We can see an improvement within phases. Particularly, phases 2' and 3 show a reduction in baseline TCT from session to session until reaching a plateau, see Fig. 6b. For phase 1 the trend for baseline TCT is slightly positive. Taking the plateau area of phase 2' into account these values seem to be on a similar level. As phase 2 has only one measurement, no trends can be seen. However, the single value is higher than in phases 1 and 2', which could indicate issues in task performance.

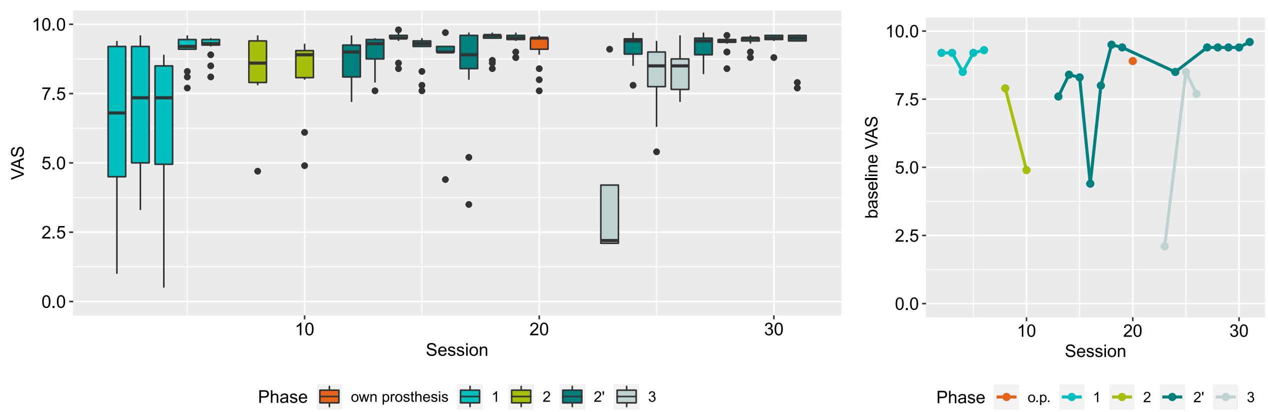
The TCT boxplots in Fig. 6a are in line with what is shown in Fig. 6b. Earlier sessions of phase 1 and 3 seem to have higher TCT values and a higher variance, which then drops towards the end of the phases. The trend seems to be less prominent in phase 2', yet earlier



(a) TCT boxplot over all tasks per session reporting the median, first and third quartile (two hinges), 1.5 inter-quartile range (two whiskers) and all "outlying" points beyond that range. To avoid distortion this plot is cropped cutting out two very high TCT-values in session 22, i.e. $TCT_{s=22,t_{2,0}} = 208.98s$ and $TCT_{s=22,t_{3,0}} = 655.41s$.

(b) Baseline values reporting the TCT for tasks $t_{2,0}$, which was performed in every session

Fig. 6 Primary assessment measure TCT with boxplot over all tasks per session and baseline values for task $t_{2,0}$



(a) VAS boxplot over all tasks per session reporting the median, first and third quartile (two hinges), 1.5 inter-quartile range (two whiskers) and all "outlying" points beyond that range

(b) Baseline values reporting the VAS for tasks $t_{2,0}$, which was performed in every session

Fig. 7 Self-assessment measure VAS with boxplot per session and baseline values for task $t_{2,0}$

sessions seem to have slightly higher values. Phase 2 again has only one measure, which is on a similar yet slightly higher level than the initial values of phase 2' taking into account the outlines of the boxplot.

Additionally, we can see from the plots in Fig. 6 that the TCT with the incremental myocontroller is on a comparable level with P using his own prosthesis. The comparison should be drawn to phase 2', since it involves the same tasks.

VAS self-assessment

The self-assessment using a VAS followed a similar behaviour as TCT, see Fig. 7. Here the satisfaction was lower in the earlier parts of a phase than towards the end. This is particularly evident in phase 1 and 3. Phase 2' contained a session that was particularly unsatisfying to P in the baseline task, see session 16 in Fig. 7b. Considering Fig. 7a, it seems that only this particular task was unsatisfying, since the remaining ones

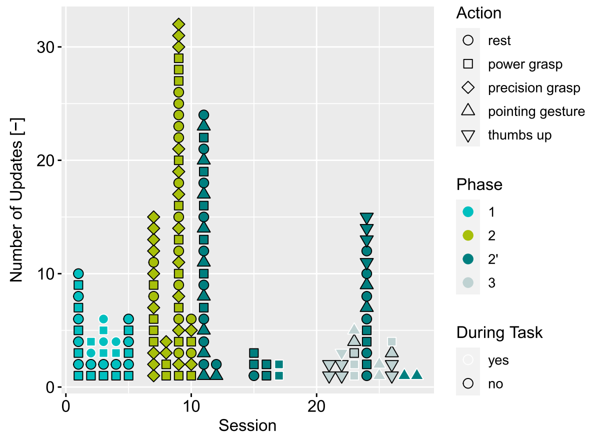


Fig. 8 Updates of the myocontrol per session. Each symbol represents one update of an action. The shape indicates the respective action, the colour during which phase the update was performed and white or black outlines indicate, whether the update was performed during a task or in between tasks, respectively

were evaluated similarly to the previous and following sessions and the VAS value for the baseline task was considered an outlier in the boxplot.

In general, the VAS assessment tended to be rather positive with 89% of its values above 7.5 and a median of 9.3. Notable exceptions were the very early sessions of phase 1. The VAS values varied heavily within one session. Starting with session 5 the self-assessment became more consistent with higher values.

All individual VAS self-assessments can be found in Table 2.

Updates

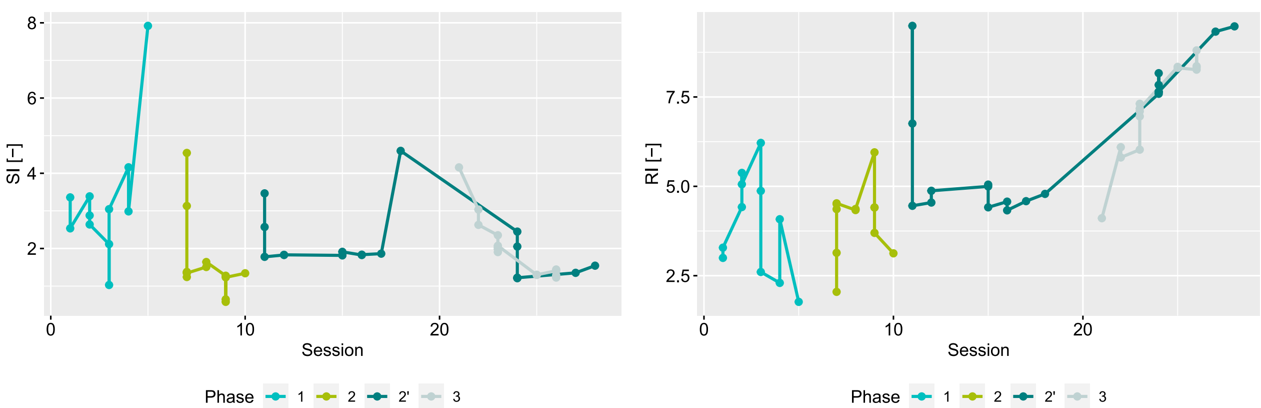
The number of updates per session can be found in Fig. 8. It depicts how many of those updates were required during the performance of a task and what action was updated.

In phase 1 regular updates were required, which indicates a level of uncertainty in a situation where only *resting pose* and *power grasp* were required. The introduction of a further action in phase 2 increased the number of updates required even further. This shows the difficulty in finding a stable control for the action set of *resting post*, *power grasp* and *precision grasp*. Eventually, this phase was aborted and after the changes to the action set, a functional training data set could be found within one session. After 24 updates in session 11 only very few additional updates were required throughout the rest of phase 2'. Notable exception here is session 24 where a retraining with 15 updates occurred. Due to an error of the experimenter a full retraining was initiated, which would not have been required. Phase 3, where the *pre-lateral grasp* was introduced, provides a further indication of confidence in the navigation of the novel myocontroller. Only five repetitions of the newly added action were required to successfully perform tasks. Compared to phases 1 and 2 the number of additional updates was rather low.

Furthermore, we would like to point out that due to the myocontrollers capability to forget obsolete training data, the amount of training data used per action was almost constant throughout the user study. The limit for repetitions per action was set to 5. For phases 1, 2 and 2′ this level was already reached in the first session of a new phase, while for phase 3 this level was reached in the second session of the phase.

EMG-data measures

Figure 9 shows the evolution of SI and RI over the course of the entire study. Different phases have been



(a) SI (b) RI

Fig. 9 SI and RI after every update to the myocontroller. Coloured lines indicate the changes within one phase. Multiple updates per session were possible resulting in multiple points per session. Not every session required updates, which led to gaps in the visualisation colour-coded and the individual values of a phase were connected with a line to better visualise the changes within each phase. For several sessions more than one value is reported. Every time a model update had been performed, SI and RI were re-evaluated. In case there were several updates per session, all values are reported.

As we have mentioned in "Incremental myocontrol algorithm", for our controller we implemented *progressive forgetting*. Obsolete repetitions of an action were discarded and therefore both SI and RI should converge to an optimal value for the user without the influence of obsolete data. As both SI and RI are measures of distance, SI should *increase*, signifying better separability between actions and RI should *decrease*, signifying higher repeatability and consistency in controlling one's muscles.

In phases 1 and 2 both SI and RI did not seem to follow a clear trend. Phase 1 ended with positive developments from a theoretical point of view, i.e. a large increase in SI and considerable drop in RI. Phase 2 started with a high separability, dropped significantly and then remained at rather low values. RI started low, increased and expressed a varying behaviour that did not resemble a clear trend. The initial decrease of SI and increase of RI were theoretically negative developments. Phase 2' started with both high SI and RI and then dropped within the first session. In the development of the RI a trend towards higher values became evident. For the SI we can see a plateau area followed by a large jump, after which a trend to lower values can be seen. This trend continued throughout phase 3 for both SI and RI.

Furthermore, we have calculated the predictive distribution for each data sample in each task of our study. Figure 10 shows the mean variance of the predictive distribution σ^2_{pred} for each task in chronological order. Different phases of the experiment have been highlighted with different colours.

Phase 1 started with higher variance until task 37 in session 5, where a large drop can be seen. Thereafter the remaining tasks of phase 1 were performed with very low σ^2_{pred} indicating high consistency in the expressed control signals by P. After the transition to phase 2 the highest σ^2_{pred}-values in the entire study can be seen. Neither a drop nor a considerable decrease was evident within this phase. The values represent a high level of uncertainty in P's control and eventually this phase was considered failed. The change in the action set that came with phase 2' led to decreased, yet still rather high values of σ^2_{pred}. These remained consistent until task 143 in session 18, where a second considerable drop can be noticed. After the second drop there were no higher values for the rest of the study. This is even true after introducing a further action in phase 3.

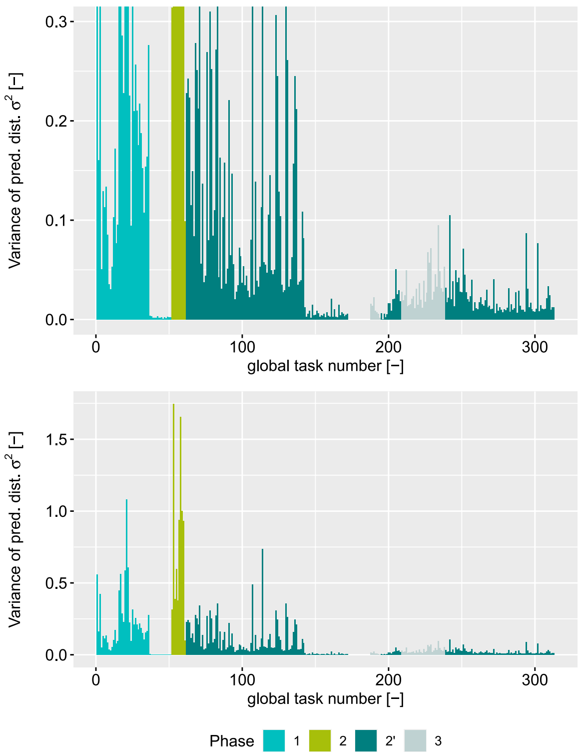


Fig. 10 Variance of the predictive distribution σ^2_{pred} averaged per task. Colour-coding indicates the phase of the experiment. The top plot has been cropped to better visualise the low end of the scale

Discussion

Using an incremental myocontroller and the SATMC P was able to learn to reliably control four actions performed by a multi-articulated hand prosthesis in daily-living tasks. At the same time, the SATMC showed its capabilities to monitor P's progress and to assess the performance of user and myocontroller. We were able to observe improvement within phases, improvement over the full study, identify failed phases, show the benefit of incremental myocontrol, and show comparable performance to using standard two-sensor control.

For both primary measures, TCT and VAS, we can see a positive development within phases. These trends can be seen particularly in the baseline task. The improvement within phases can also be seen in the predictive variance σ^2_{pred}. Here, phases 1 and 2' are of particular interest as in both cases a substantial drop can be seen. These measures indicate that the beginning of a phase required more effort and learning from P and within a few sessions improvement could be observed. Interestingly, the improvement in session 5 of phase 1 can be seen in both VAS and σ^2_{pred}. The VAS self-assessment until session 4 showed considerable variance indicating a

Table 2 Self-assessment of all tasks using a VAS

Session	Task	VAS	Task	VAS	Task	VAS
2	$t_{1,0}$	9.4	$t_{1,2}$	7.9	$t_{1,4}$	2.9
	$t_{2,0}$	9.2	$t_{2,2}$	5.7	$t_{2,3}$	3.0
	$t_{3,0}$	5.0	$t_{3,1}$	9.0	$t_{3,3}$	3.3
	$t_{4,0}$	9.4	$t_{4,2}$	9.2	$t_{4,4}$	6.8
	$t_{5,0}$	1.0	$t_{5,0}$	5.0	$t_{5,1}$	7.9
3	$t_{1,0}$	9.2	$t_{1,2}$	5.9		
	$t_{2,0}$	9.2	$t_{2,2}$	3.9		
	$t_{3,0}$	9.3	$t_{3,2}$	9.6		
	$t_{4,0}$	5.0	$t_{4,1}$	5.0		
	$t_{5,0}$	9.2	$t_{5,2}$	NaN		
4	$t_{1,0}$	8.7	$t_{1,2}$	5.0	$t_{1,3}$	0.5
	$t_{2,0}$	8.5	$t_{2,2}$	8.9	$t_{2,4}$	0.5
	$t_{3,0}$	7.7	$t_{3,2}$	8.5	$t_{3,4}$	NaN
	$t_{4,0}$	4.8	$t_{4,1}$	5.4	$t_{4,2}$	NaN
	$t_{5,0}$	8.3	$t_{5,2}$	7.0	$t_{5,4}$	NaN
5	$t_{1,0}$	7.7	$t_{1,2}$	8.3	$t_{1,4}$	9.1
	$t_{2,0}$	9.2	$t_{2,2}$	9.6	$t_{2,4}$	9.5
	$t_{3,0}$	9.2	$t_{3,2}$	9.6	$t_{3,4}$	9.4
	$t_{4,0}$	9.2	$t_{4,2}$	8.1	$t_{4,4}$	9.2
	$t_{5,0}$	9.1	$t_{5,2}$	9.5	$t_{5,4}$	9.2
6	$t_{1,0}$	9.3	$t_{1,2}$	9.5	$t_{1,4}$	9.4
	$t_{2,0}$	9.3	$t_{2,2}$	9.5	$t_{2,4}$	9.4
	$t_{3,0}$	8.1	$t_{3,2}$	9.5	$t_{3,4}$	9.3
	$t_{4,0}$	8.9	$t_{4,2}$	9.3	$t_{4,4}$	8.5
	$t_{5,0}$	9.3	$t_{5,2}$	9.2	$t_{5,4}$	9.5
8	$t_{4,5}$	7.9	$t_{4,2}$	9.2		
	$t_{2,0}$	7.9	$t_{2,2}$	8.0		
	$t_{6,0}$	9.6	$t_{6,2}$	9.4		
	$t_{7,0}$	9.6	$t_{7,2}$	9.4		
	$t_{8,0}$	7.8	$t_{8,1}$	4.7		
10	$t_{4,0}$	8.3	$t_{4,2}$	6.1		
	$t_{2,0}$	4.9	$t_{2,1}$	9.3		
	$t_{6,0}$	8.9	$t_{6,2}$	9.1		
	$t_{7,0}$	8.9	$t_{7,2}$	8.0		
	$t_{5,0}$	8.9	$t_{5,2}$	9.3		
12	$t_{9,0}$	9.1	$t_{9,0}$	9.2		
	$t_{9,1}$	7.7	$t_{9,1}$	8.4		
	$t_{9,2}$	9.4	$t_{9,2}$	9.0		
	$t_{9,3}$	9.6	$t_{9,3}$	9.3		
	$t_{9,1}$	8.9	$t_{9,4}$	7.8		
	$t_{9,4}$	7.2				
13	$t_{2,0}$	7.6	$t_{2,1}$	9.1	$t_{2,3}$	7.9
	$t_{4,0}$	9.5	$t_{4,2}$	9.3	$t_{4,4}$	9.5
	$t_{5,0}$	9.4	$t_{5,2}$	9.2	$t_{5,4}$	9.4
	$t_{9,0}$	9.5	$t_{9,2}$	8.2	$t_{9,4}$	8.4
	$t_{13,0}$	9.5	$t_{13,2}$	9.2	$t_{13,3}$	9.4
14	$t_{2,0}$	8.4	$t_{2,2}$	9.5	$t_{2,4}$	8.6
	$t_{4,0}$	9.5	$t_{4,2}$	9.6	$t_{4,4}$	9.8
	$t_{5,0}$	9.5	$t_{5,2}$	9.4	$t_{5,4}$	9.7
	$t_{9,0}$	9.5	$t_{9,2}$	9.5	$t_{9,4}$	9.7
	$t_{13,0}$	9.5	$t_{13,2}$	9.5	$t_{13,3}$	9.6
15	$t_{2,0}$	8.3	$t_{2,2}$	7.8	$t_{2,3}$	7.6
	$t_{4,0}$	9.3	$t_{4,2}$	9.3	$t_{4,4}$	9.4
	$t_{5,0}$	9.2	$t_{5,2}$	9.2	$t_{5,4}$	9.5
	$t_{9,0}$	9.4	$t_{9,2}$	9.3	$t_{9,4}$	9.3
	$t_{13,0}$	9.5	$t_{13,2}$	9.3	$t_{13,3}$	9.5
16	$t_{2,0}$	4.4	$t_{2,2}$	NaN		
	$t_{4,0}$	9.0	$t_{4,2}$	NaN		
	$t_{5,0}$	9.2				
	$t_{9,0}$	9.0				
	$t_{13,0}$	9.7				
⋮	⋮	⋮	⋮	⋮	⋮	⋮
17	$t_{2,0}$	8.0	$t_{2,2}$	5.2	$t_{2,3}$	3.5
	$t_{4,0}$	9.6	$t_{4,2}$	8.9	$t_{4,4}$	9.7
	$t_{5,0}$	9.3	$t_{5,2}$	8.8	$t_{5,4}$	9.6
	$t_{9,0}$	8.0	$t_{9,2}$	8.8	$t_{9,4}$	9.7
	$t_{13,0}$	9.6	$t_{13,2}$	8.8	$t_{13,3}$	9.7
18	$t_{2,0}$	9.5	$t_{2,2}$	9.5	$t_{2,4}$	9.5
	$t_{4,0}$	9.6	$t_{4,2}$	9.5	$t_{4,4}$	9.7
	$t_{5,0}$	9.6	$t_{5,2}$	9.6	$t_{5,4}$	9.6
	$t_{9,0}$	8.6	$t_{9,2}$	8.4	$t_{9,4}$	8.7
	$t_{13,0}$	9.6	$t_{13,2}$	9.6	$t_{13,3}$	9.6
19	$t_{2,0}$	9.4	$t_{2,2}$	9.6	$t_{2,4}$	9.5
	$t_{4,0}$	9.5	$t_{4,2}$	9.7	$t_{4,4}$	9.5
	$t_{5,0}$	9.5	$t_{5,2}$	9.6	$t_{5,4}$	9.5
	$t_{9,0}$	8.8	$t_{9,2}$	9.0	$t_{9,4}$	8.8
	$t_{13,0}$	9.7	$t_{13,2}$	9.6	$t_{13,3}$	9.6
20	$t_{2,0}$	8.9	$t_{2,2}$	7.6	$t_{2,4}$	8.0
	$t_{4,0}$	9.5	$t_{4,2}$	9.6	$t_{4,4}$	9.5
	$t_{5,0}$	9.4	$t_{5,2}$	9.6	$t_{5,4}$	9.3
	$t_{9,0}$	9.5	$t_{9,2}$	9.5	$t_{9,4}$	8.4
	$t_{13,0}$	9.5	$t_{13,2}$	9.5	$t_{13,3}$	9.5
23	$t_{2,0}$	2.1				
	$t_{4,0}$	2.2				
	$t_{5,0}$	4.2				
	$t_{9,0}$	2.1				
	$t_{13,0}$	9.1				
24	$t_{2,0}$	8.5	$t_{2,4}$	9.4		
	$t_{4,0}$	9.0	$t_{4,4}$	8.9		
	$t_{5,0}$	9.5	$t_{5,4}$	9.4		
	$t_{9,0}$	7.8	$t_{9,4}$	9.4		
	$t_{13,0}$	9.7	$t_{13,3}$	9.6		
25	$t_{2,0}$	8.5	$t_{2,2}$	9.0	$t_{2,4}$	8.4
	$t_{4,0}$	8.7	$t_{4,2}$	8.1	$t_{4,4}$	8.3
	$t_{5,0}$	9.4	$t_{5,2}$	9.4	$t_{5,4}$	9.1
	$t_{9,0}$	5.4	$t_{9,1}$	6.3	$t_{9,2}$	9.0
	$t_{13,0}$	6.6	$t_{13,1}$	7.4	$t_{13,2}$	9.0
26	$t_{2,0}$	7.7	$t_{2,2}$	8.6	$t_{2,4}$	7.6
	$t_{4,0}$	7.5	$t_{4,2}$	7.6	$t_{4,4}$	8.6
	$t_{5,0}$	8.1	$t_{5,2}$	9.4	$t_{5,4}$	8.9
	$t_{9,0}$	8.1	$t_{9,2}$	8.5	$t_{9,4}$	8.5
	$t_{13,0}$	7.2	$t_{13,2}$	9.4	$t_{13,3}$	9.6
27	$t_{2,0}$	9.4	$t_{2,2}$	9.6	$t_{2,4}$	9.6
	$t_{4,0}$	8.7	$t_{4,2}$	8.8	$t_{4,4}$	9.4
	$t_{5,0}$	9.5	$t_{5,2}$	9.1	$t_{5,4}$	9.3
	$t_{9,0}$	9.0	$t_{9,2}$	9.5	$t_{9,4}$	8.8
	$t_{13,0}$	9.7	$t_{13,2}$	9.5	$t_{13,3}$	8.2
28	$t_{2,0}$	9.4	$t_{2,2}$	9.3	$t_{2,4}$	9.5
	$t_{4,0}$	9.4	$t_{4,2}$	9.0	$t_{4,4}$	9.4
	$t_{5,0}$	9.0	$t_{5,2}$	9.6	$t_{5,4}$	9.4
	$t_{9,0}$	8.4	$t_{9,2}$	9.5	$t_{9,4}$	9.4
	$t_{13,0}$	9.5	$t_{13,2}$	9.4	$t_{13,3}$	9.4
29	$t_{2,0}$	9.4	$t_{2,2}$	9.5	$t_{2,4}$	9.5
	$t_{4,0}$	8.8	$t_{4,2}$	9.5	$t_{4,4}$	9.6
	$t_{5,0}$	9.5	$t_{5,2}$	9.5	$t_{5,4}$	9.5
	$t_{9,0}$	9.4	$t_{9,2}$	9.4	$t_{9,4}$	9.0
	$t_{13,0}$	9.3	$t_{13,2}$	9.4	$t_{13,3}$	9.5
30	$t_{2,0}$	9.4	$t_{2,2}$	9.6	$t_{2,4}$	9.6
	$t_{4,0}$	9.4	$t_{4,2}$	9.5	$t_{4,4}$	9.6
	$t_{5,0}$	9.4	$t_{5,2}$	9.6	$t_{5,4}$	9.6
	$t_{9,0}$	8.8	$t_{9,2}$	9.5	$t_{9,4}$	9.5
	$t_{13,0}$	9.5	$t_{13,2}$	9.5	$t_{13,3}$	9.6
31	$t_{2,0}$	9.6	$t_{2,2}$	9.6	$t_{2,4}$	7.7
	$t_{4,0}$	9.6	$t_{4,2}$	9.6	$t_{4,4}$	9.4
	$t_{5,0}$	9.4	$t_{5,2}$	9.6	$t_{5,4}$	9.5
	$t_{9,0}$	9.5	$t_{9,2}$	9.6	$t_{9,4}$	9.5
	$t_{13,0}$	7.9	$t_{13,2}$	9.4	$t_{13,3}$	9.5

VAS values are colour-coded between black VAS $= 0$ (poor evaluation) and white for VAS $= 10$ (good evaluation); the colour in the *session* column indicates the phase varying level of satisfaction with the performance. High σ^2_{pred}-values indicate uncertainty in the myocontrol, as well. With the update in session 5 σ^2_{pred} and the variance of the VAS self-assessment both decreased. The average VAS for session 5 was very high, which indicated satisfaction and low σ^2_{pred} indicated high certainty in the usage of the myocontrol. This suggests that with the update in session 5 a suitable training dataset had been found and the lack of further updates indicated a stable and reliable myocontrol. This initial period of the study could have been an explorative period for P. Since P is a user of a prosthesis with direct control, switching to ML-based myocontrol could have initially required a high effort. Note that from the outset the myocontroller of the experiment was different from the myocontroller P used in his daily life.

The following phase 2 showed that an increase in myocontroller complexity required further training. However, the choice of action proved to be too demanding and a switch in the action set was required to continue with the user study.

Phase 2' started similarly to phase 1. Decrease in TCT and increase in VAS values in the first sessions indicated improvement in the beginning, although with lower variance in the self-assessment as in phase 1. A further milestone marks session 18: after task 143 there was a substantial second drop in the variance of the predictive distribution σ^2_{pred}. Both instances where σ^2_{pred} dropped considerably and remained low for a certain period exhibited a considerable increase in SI, as well. The RI on the other hand dropped with the first σ^2_{pred}-drop and remained on a similar level with the second one. For SI, these are the two largest changes in the entire user study and seem to align very well with good performance. However, the remaining trend of SI towards lower values following the increase does not support the claim of correlation between good performance and a high SI [55, 59, 60]. The very last model used in the study even had a lower SI than the value before the drop in σ^2_{pred}. Although non-conclusive, these findings are in line with what has been reported in literature regarding SI and RI and other offline measures [18, 20, 21].

Since after the second σ^2_{pred}-drop, there were no tasks with high values for σ^2_{pred} for the rest of the study, this could indicate the beginning of another period for P. It could be argued that at this point P became proficient in the usage of ML-based myocontrol and an understanding of the myocontroller was established. The addition of a further action in phase 3 did not lead to uncertainty in the usage of the myocontroller. Yet P needed to adapt to the new myocontroller, which is apparent from the improvements in baseline TCT and baseline VAS, see Figs. 6b and 7b.

These two jumps could indicate three different periods in the improvement over the course of the study. First a familiarisation period, followed by a learning period and ending with a proficient adaptation period.

Two further points support the notion of reaching a proficient state. First, the performance in the second baseline measure, session 20 with P's own prosthesis, is on a comparable level as the ML-based myocontroller. Under the assumption that P is proficient with his own prosthesis he could have reached a certain level of proficiency with the ML-based myocontroller as well. Switching from a familiar control modality to a more complex, yet more capable one can initially result in a reduced performance [40]. Even after 7 training sessions it was reported that people achieved better results with their own prothesis than with ML-based ones [26]. Second, the erroneously performed retraining in session 24 did not appear to have an impact on the performance, i.e. TCT, VAS or σ^2_{pred}. One could argue that P's performance didn't originate from *accidentally* good data, but that P learned to *consistently* produce good signals to pilot the prosthesis and myocontroller.

Incrementality

Incrementality played a key role in learning to use the myocontroller and in dealing with challenging situations.

There was no need for a separate training of sEMG-signals focused on separateness and repeatability, a process that commonly is required in learning to use a ML-based prosthesis. Exemplary duration of this process is 7–10 h over 5–7 session [26, 28]. The exact values vary considerably based on the individual person. Taken the two milestones of P in session 5 (after 1 month) and 18 (around the 7th month) into account, the training time can be considered longer. However, prosthesis fitting and training is most important in the first six months after amputation [61]. The fact that from the first session training involved functional tasks while wearing a prosthesis, could support prosthetist acceptance.

During P's training, an update consisted of 2.7 repetitions on average, which includes the instances of full retraining. A full retraining would consist of five repetitions per action. In phase 1 this would be 10 repetitions and 20 repetitions in phase 3. This results in a considerable amount of time saved on individual updates when using an incremental myocontrol algorithm. Furthermore, updates were often asked for by P to make a certain action more stable or improve the performance in a specific situation. In our opinion, the threshold for issuing a small update is lower than issuing a full retraining.

This could lead to faster learning and a better adaptation, and thus faster improvement in performance.

The combination of training only on the sustained part of an action and incremental updates further helped in dealing with the limb position effect. Instead of initially training in multiple positions to cover all required postural variations, updates could be issued in challenging positions only when required. Training on the sustained part of an action does not require the participant to follow a specific trajectory, however, an action has to be maintained at a strong but comfortable level of force. This allowed P to maintain exactly in the pose, where the myocontroller reached its limits, and update the training data with highly specific information to improve the myocontroller.

The capability of the RR-RFF-based myocontroller to add actions incrementally, reduced the calibration effort for P additionally. This effect became relevant at a later point in the user study, when P transitioned from phase 2' to phase 3. Instead of requiring a full retraining only the new action had to be updated and P could continue with performing tasks.

A further testament to the robustness of the RR-RFF-based myocontroller is the fact that over the course of the study there were several instances where P did not require any update over several sessions. Hence, for multiple visits involving donning and doffing of the prosthesis no changes to the myocontroller were required and all tasks could be performed satisfactorily. In addition to that we want to highlight that no initial training after donning the prosthesis was issued at the beginning of a session.

SATMC protocol

ML-based myocontrollers are intuitive in terms of the type of sEMG-signals that are required for training the algorithm. However, learning to pilot such a myocontroller reliably has proven to be challenging, lengthy, and not necessarily intuitive for many users. The SATMC appears to be a promising tool for assessing ML-based myocontrollers and training users in their usage. Supported by the structured multi-phased approach a gradual improvement was possible for P. Due to the usage of tasks of different levels of complexity, training was possible at a level comfortable for the participant. In "Simultaneous assessment and training of myoelectric control (SATMC)" we have formulated four aspects that should be fulfilled for an adequate assessment and training of ML-based myocontrol. These were repeatability and increasing difficulty (A1), postural variation during tasks (A2), multiple actions per task (A3), and a short familiarisation time for the rater (A4). In the user study P attempted scenarios with different levels of difficulty. Expressing a level of satisfaction through the VAS assessment confirms that A1 was successfully implemented. A number of tasks involved larger distances that needed to be covered, i.e. wrist rotation and height differences. These variations adequately cover the postural variation required in A2. Changes between different grasps were part of several of the tasks, which satisfied A3. Regarding A4, easy to acquire measures, i.e. VAS and TCT, have been introduced, which simplified the tasks of the experimenter. However, a number of errors occurred on the side of the experimenter, where instructions were not given correctly. As the SATMC has grown to cover as many relevant features as possible, the complexity of performing a study using the protocol increased over its development. Here, we believe that the initial level of simplicity intended for the SATMC has not been fully reached.

During the user study and in its evaluations two potential improvements to the SATMC have been identified. First, as stated in "User study" no initial training in a session was required, since the model from the previous session could be reloaded and reused directly. This beneficial feature is not reflected in any measure besides the number of updates. A solution could be adding to the 15 tasks an initial *calibration stage* that is timed and in case no initial training is required set to $0s$.

Second, since phase 2 was considered failed, a measure to determine at what point a phase can be considered failed could be useful. One option could be based on the VAS evaluation of the user. However, the evaluation of sessions 8 and 10 in phase 2 was overly positive[1]. A second option could be a threshold on the variance of the predictive distribution σ^2_{pred}. The highest values of σ^2_{pred} were measured in phase 2. This is only feasible, if the ML method allows for the calculation of the predictive distribution. Another option could be to use the number of updates required during a session. The failed phase contained the session with the highest number of updates in the entire study. A threshold on the number of updates could help identify failed phases.

With the structure and repetition that the SATMC introduces, we also introduce the risk of learning specific tasks rather than acquiring general motor skills. At the beginning of a phase five tasks are chosen by the person administering the SATMC and in each session the participant starts with the basic variants of these tasks. However, the fact that at the beginning of phase 2' P only required a few repetitions to learn a new action compared to many repetitions in all previous phases, could

[1] For session 8 VAS evaluations by P are available, but no TCT values, see Figs. 6a and 7a. Unfortunately, the data was lost.

indicate motor skill acquisition rather than task-specific learning, see Fig. 8. On the other hand, we also introduce variability with the SATMC. Depending on the skill of the participant different variants of these tasks are executed throughout a phase. Earlier session will likely involve easier task variants, while the last session will involve the most difficult ones. This variance potentially affects our primary measure TCT. Considering Fig. 6, we can see initially large values of TCT for phases 2' and 3 followed by a plateau area. The low variance in the plateau area could indicate that influence of the task variants is small.

With these improvements we see a high potential of the SATMC to be applied in clinical use. Since training and assessment are both part of the SATMC training the participant to produce good sEMG-signals and functional assessment of prosthesis both occur at the same time. The user would start earlier with performing tasks with their prosthesis, which could have beneficial effects on motivation and acceptance. Furthermore, a number of steps in the SATMC can be automated as they follow strict guidelines, see "Guidelines". This would reduce the burden on the person administering the SATMC and therefore increase the clinical applicability. In addition, the SATMC is not restricted to training the use of hand prostheses but can also be used to train more proximal prosthesis joints.

Limitations

During the analysis of the results we were able to identify some limitations of the user study with P. In phases 2' and 3 the SI exhibited a trend towards values indicating poorer training data quality, yet the participant improved and was more satisfied. As SI and RI are pure *offline* measures and TCT and VAS are *online* measures (with the user in the loop), a mismatch between them is a common phenomenon. A further possible explanation could be the way training data was gathered. The user is encouraged to update the myocontroller, when instabilities occur in the control. These instabilities could originate from changes in the muscle and limb orientation, i.e. limb position effect. An update will therefore contain data that is rather different from what was present in the training data before the update. This could lead to an increase in RI, since the update is labelled with the action that was updated without taking specific information of the position into account. A larger spread of the action cluster (containing all repetitions) would be the result and hence potentially lead to a lower SI. In general, a higher level of repeatability, as in being able to precisely reproduce a muscle signal, is a desirable feature. However, based on the training protocol RI and SI could potentially reflect a different measure than the intended separability and repeatability. On the other hand, both drops in the values of the variance of the predictive distribution σ^2_{pred} coincided with an increase in SI as one would expect.

Furthermore, we have identified some general improvements for the SATMC. A comparison to different validated assessment method, such as the ones described in In "Simultaneous assessment and training of myoelectric control (SATMC)", would have strengthened the results of this user study. The administration of validated assessment tools at regular intervals of the user study, e.g. at the beginning and end of a phase, would have provided further insights in the validity of the SATMC. We see such an addition as useful for future studies based on the SATMC.

Additionally, some unfortunate mistakes by the experimenter were made during the user study. For one, phase 2' was continued longer than it should have been. In sessions 13 and 15 the VAS scores were evaluated wrongly, which led to single-step increases in task variants instead of two-step increases. A correct decision in either of these sessions would have led to an earlier successful conclusion of phase 2'. Additionally, experimenter errors occurred in session 24, session 27 and the session thereafter: the experimenter gave instructions regarding the wrong phase. While the instructions were instances of phase 2', they should have been instances of phase 3 according to the SATMC guidelines. Although unfortunate, in our opinion additional repetitions of a phase should not severely impact the overall conclusions drawn from this study. We believe that all errors regarding wrong VAS evaluation or wrong phase selection could be avoided by automating the SATMC. This could be achieved in form of a specific software that provides directions based the data acquired. This would also be a step towards aspect A4, defined in the beginning of "Simultaneous assessment and training of myoelectric control (SATMC)". On the other hand, the unnecessary full retraining that occurred, which we considered an error, would not profit from this measure, since no strict guidelines were designed regarding updates. The user or the experimenter decide whether they are required.

Another limiting factor in this user study is the involvement of only one participant. To minimise the impact of this factor, we have used SCED in the design of the SATMC and the user study. SCED provides guidelines for performing structured experiments involving only a small number of participants. Methods such as direct replication and the introduction of a baseline, help in lowering the impact of a low number of participants. We have implemented these two methods by incrementally changing the set of actions and by choosing a specific task that remains unchanged for the entire user study.

Finally, in its current form the tasks incorporated in the SATMC are not validated. The current paper describes a first proposal to train and assess myoelectric control. Further development of the SATMC protocol might require validation studies. For example, a Rasch analysis could verify that the task variants are indeed increasing in difficulty. Additionally, a validation study should include investigations how the outcome measures TCT and VAS are affected by the variance within a phase due to potentially different task variants between sessions.

Conclusion

By the end of the user study P was able to achieve proportional myocontrol of four actions with a multi-articulated prosthetic hand using the incremental RR-RFF-based myocontroller. He was naive to such a control modality at the beginning of the study. Supported by the directions realised in the simultaneous training and assessment of the SATMC he succeeded in reaching a dexterous myocontrol in ADL-like tasks. The incrementality in both the myocontroller and the SATMC allowed P to progress at a level comfortable for him.

As the SATMC can be applied independent of the myocontroller, the protocol can be used in future studies to train a user in ML-based myocontrol and assess novel myocontrol approaches. This in turn will provide more validity to the SATMC and lead to results allowing for comparisons between ML-based myocontrollers.

Abbreviations

ACMC	Assessment of Capacity for Myoelectric Control
ADLs	Activities of daily living
CRT	Clothespin Relocation Test
DOFs	Degrees of freedom
EMG	Electromyography
ML	Machine-learning
P	Participant
RI	Repeatability Index
RR-RFF	Ridge Regression with Random Fourier Features
SATMC	Simultaneous Assessment and Training of Myoelectric Control
SCED	Single-Case Experimental Design
sEMG	Surface electromyography
SHAP	Southampton Hand Assessment Procedure
SI	Separability Index
TCT	Task completion time
VAS	Visual analogue scale

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Authors contributions

Conceptualisation: MN, CC, RB, CvS; Data curation: MN; Formal Analysis: MN; Investigation: MN, CC,; Methodology: MN, CC, RB, CvS; Project administration: CC, AA; Software: MN, CC; Supervision: CC; Validation: RB, CvS; Visualisation: MN.; Writing—original draft: MN; Writing— review & editing: MN, CC, RB, CvS, AA; All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

This study was formally approved by the host institution's internal committee for data protection (ASDA 14/05 TOP 6.5 on 02.09.2014) and it followed the guidelines of the World Medical Association's declaration of Helsinki.

Consent for publication

The participant gave consent for publication of anonymised data as part of the informed consent form signed prior to the study.

Competing interests

The authors declare that they have no competing interests.

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References

1. Beckerle P, Castellini C, Lenggenhager B. Robotic interfaces for cognitive psychology and embodiment research: a research roadmap. WIREs Cogn Sci. 2019;10(2):1486. https://doi.org/10.1002/wcs.1486.
2. Hargrove LJ, Li G, Englehart KB, Hudgins BS. Principal components analysis preprocessing for improved classification accuracies in pattern-recognition-based myoelectric control. IEEE Trans Biomed Eng. 2009;56(5):1407–14. https://doi.org/10.1109/TBME.2008.2008171.
3. Ison M, Vujaklija I, Whitsell B, Farina D, Artemiadis P. High-density electromyography and motor skill learning for robust long-term control of a 7-DoF Robot Arm. IEEE Trans Neural Syst Rehabil Eng. 2016;24(4):424–33. https://doi.org/10.1109/TNSRE.2015.2417775.
4. Kapelner T, Negro F, Aszmann OC, Farina D. Decoding motor unit activity from forearm muscles: perspectives for myoelectric control. IEEE Trans Neural Syst Rehabil Eng. 2018;26(1):244–51. https://doi.org/10.1109/TNSRE.2017.2766360.
5. De Luca CJ, Chang S-S, Roy SH, Kline JC, Nawab SH. Decomposition of surface EMG signals from cyclic dynamic contractions. J Neurophysiol. 2014;113(6):1941–51. https://doi.org/10.1152/jn.00555.2014.
6. Côté-Allard U, Campbell E, Phinyomark A, Laviolette F, Gosselin B, Scheme E. Interpreting deep learning features for myoelectric control: a comparison with handcrafted features. Front Bioeng Biotechnol. 2020;8:158. https://doi.org/10.3389/fbioe.2020.00158.
7. Connan M, RuizRamírez E, Vodermayer B, Castellini C, Assessment of a Wearable Force- and Electromyography Device and Comparison of the Related Signals for Myocontrol. Front Neurorobot. 10 (2016). https://doi.org/10.3389/fnbot.2016.00017
8. Nowak M, Eiband T, Ruiz Ramírez E, Castellini C. Action interference in simultaneous and proportional myocontrol: comparing force- and

electromyography. J Neural Eng. 2020;17(2). https://doi.org/10.1088/1741-2552/ab7b1e.
9. Connan M, Kõiva R, Castellini C. Online natural myocontrol of combined hand and wrist actions using tactile myography and the biomechanics of grasping. Front Neurorobot. 2020;14:11. https://doi.org/10.3389/fnbot.2020.00011.
10. Jiang X, Merhi L-K, Xiao ZG, Menon C. Exploration of force myography and surface electromyography in hand gesture classification. Med Eng Phys. 2017;41:63–73. https://doi.org/10.1016/j.medengphy.2017.01.015.
11. Castellini C, Hertkorn K, Sagardia M, González DS, Nowak M, A virtual piano-playing environment for rehabilitation based upon ultrasound imaging. In: 5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics, pp. 548–554; 2014. https://doi.org/10.1109/BIOROB.2014.6913835
12. McIntosh J, Marzo A, Fraser M, Phillips C, EchoFlex: Hand Gesture Recognition using Ultrasound Imaging. In: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, pp. 1923–1934. ACM, Denver Colorado USA; 2017. https://doi.org/10.1145/3025453.3025807
13. Zhang Y, Harrison C, Tomo: Wearable, Low-Cost Electrical Impedance Tomography for Hand Gesture Recognition. In: Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology, pp. 167–173. ACM, Charlotte NC USA; 2015. https://doi.org/10.1145/2807442.2807480
14. Zhang Y, Xiao R, Harrison C, Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography. In: Proceedings of the 29th Annual Symposium on User Interface Software and Technology, pp. 843–850. ACM, Tokyo Japan; 2016. https://doi.org/10.1145/2984511.2984574
15. Scott RN, Parker PA. Myoelectric prostheses: state of the art. J Med Eng Technol. 1988;12(4):143–51. https://doi.org/10.3109/03091908809030173.
16. COAPT LLC: complete control system GEN2. https://coaptengineering.com/wp-content/uploads/2021/09/Coapt-Gen2-Handbook-v5.2.pdf; 2021.
17. Ottobock: Technology for People 4.0: Ottobock at OTWorld 2018. https://www.ottobock.com/en/newsroom/news/technology-for-people-4-0-ottobock-at-otworld-2018.html. Accessed 08 Oct 2020; 2018.
18. Jiang N, Dosen S, Muller K-R, Farina D. Myoelectric control of artificial limbs—is there a need to change focus? [In the Spotlight]. IEEE Signal Process Mag. 2012;29(5):152–150. https://doi.org/10.1109/MSP.2012.2203480.
19. Muceli S, Jiang N, Farina D. Extracting signals robust to electrode number and shift for online simultaneous and proportional myoelectric control by factorization algorithms. IEEE Trans Neural Syst Rehabil Eng. 2014;22(3):623–33. https://doi.org/10.1109/TNSRE.2013.2282898.
20. Teh Y, Hargrove LJ, Offline Repeatability Correlates with Real-Time Performance of Pattern Recognition Controllers. In: ICNR 2020, p. 2 (2020)
21. Franzke AW, Kristoffersen MB, Jayaram V, Sluis CKVD, Murgia A, Bongers RM, Exploring the relationship between EMG feature space characteristics and control performance in machine learning myoelectric control. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 1–1 (2020). https://doi.org/10.1109/TNSRE.2020.3029873
22. Kristoffersen MB, Franzke AW, Van Der Sluis CK, Murgia A, Bongers RM. The Effect of Feedback During Training Sessions on Learning Pattern-Recognition-Based Prosthesis Control. IEEE Trans Neural Syst Rehabil Eng. 2019;27(10):2087–96. https://doi.org/10.1109/TNSRE.2019.2929917.
23. Nowak M, Castellini C. The LET Procedure for Prosthetic Myocontrol: Towards Multi-DOF Control Using Single-DOF Activations. PLoS ONE. 2016;11(9):0161678. https://doi.org/10.1371/journal.pone.0161678.
24. Nowak M, Vujaklija I, Sturma A, Castellini C, Farina D, Simultaneous and Proportional Real-Time Myocontrol of up to Three Degrees of Freedom of the Wrist and Hand. IEEE Transactions on Biomedical Engineering, 1–12 (2022). https://doi.org/10.1109/TBME.2022.3194104
25. Gigli A, Gijsberts A, Castellini C. The Merits of Dynamic Data Acquisition for Realistic Myocontrol. Frontiers in Bioengineering and Biotechnology. 2020;8:361. https://doi.org/10.3389/fbioe.2020.00361.
26. Kristoffersen MB, Franzke AW, Bongers RM, Wand M, Murgia A, Van Der Sluis CK. User training for machine learning controlled upper limb prostheses: A serious game approach. J Neuroeng Rehabil. 2021;18(1):32. https://doi.org/10.1186/s12984-021-00831-5.
27. Franzke AW, Kristoffersen MB, Bongers RM, Murgia A, Pobatschnig B, Unglaube F, Van Der Sluis CK. Users' and therapists' perceptions of myoelectric multi-function upper limb prostheses with conventional and pattern recognition control. PLoS ONE. 2019;14(8):0220899. https://doi.org/10.1371/journal.pone.0220899.
28. Resnik L, Huang HH, Winslow A, Crouch DL, Zhang F, Wolk N. Evaluation of EMG pattern recognition for upper limb prosthesis control: A case study in comparison with direct myoelectric control. J Neuroeng Rehabil. 2018;15(1):23. https://doi.org/10.1186/s12984-018-0361-3.
29. Kuiken TA, Miller LA, Turner K, Hargrove LJ. A Comparison of Pattern Recognition Control and Direct Control of a Multiple Degree-of-Freedom Transradial Prosthesis. IEEE Journal of Translational Engineering in Health and Medicine. 2016;4:1–8. https://doi.org/10.1109/JTEHM.2016.2616123.
30. Scheme E, Fougner A, Stavdahl Ø, Chan ADC, Englehart K, Examining the adverse effects of limb position on pattern recognition based myoelectric control. In: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, pp. 6337–6340. IEEE, Buenos Aires (2010). https://doi.org/10.1109/IEMBS.2010.5627638
31. Campbell E, Phinyomark A, Scheme E. Current trends and confounding factors in myoelectric control: limb position and contraction intensity. Sensors. 2020;20(6):1613. https://doi.org/10.3390/s20061613.
32. Gijsberts A, Bohra R, SierraGonzález D, Werner A, Nowak M, Caputo B, Roa MA, Castellini CPD, Stable myoelectric control of a hand prosthesis using non-linear incremental learning. Front Neurorobot. 2014; 8. https://doi.org/10.3389/fnbot.2014.00008
33. Strazzulla I, Nowak M, Controzzi M, Cipriani C, Castellini C. Online bimanual manipulation using surface electromyography and incremental learning. IEEE Trans Neural Syst Rehabil Eng. 2017;25(3):227–34. https://doi.org/10.1109/TNSRE.2016.2554884.
34. Schiel F, Hagengruber A, Vogel J, Triebel R Incremental learning of EMG-based control commands using Gaussian Processes. In: 4th Conference on Robot Learni, p. 10; 2020.
35. Kyberd PJ. Outcome measures. In: Aszmann OC, Farina D, editors. Bionic limb reconstruction. Cham: Springer International Publishing; 2021. p. 57–74.
36. Nowak M, Bongers RM, van der Sluis CK, Castellini C, Introducing a novel training and assessment protocol for pattern matching in myocontrol: case-study of a trans-radial amputee. In: Proceedings of MEC-Myoelectric Control Symposium. 2017.
37. Tate RL, Perdices M, Rosenkoetter U, Shadish W, Vohra S, Barlow DH, Horner R, Kazdin A, Kratochwill T, Mcdonald S, Sampson M, Shamseer L, Togher L, Albin R, Backman C, Douglas J, Evans JJ, Gast D, Manolov R, Mitchell G, Nickels L, Nikles J, Ownsworth T, Rose M, Schmid CH, Wilson B. The Single-Case Reporting Guideline In BEhavioural Interventions (SCRIBE) 2016 Statement. Phys Ther. 2016;96(7):1–10. https://doi.org/10.2522/ptj.2016.96.7.e1.
38. Krasny-Pacini A, Evans J. Single-case experimental designs to assess intervention effectiveness in rehabilitation: a practical guide. Ann Phys Rehabil Med. 2018;61(3):164–79. https://doi.org/10.1016/j.rehab.2017.12.002.
39. Smith JD. Single-case experimental designs: a systematic review of published research and current standards. Psychol Methods. 2012;17(4):510–50. https://doi.org/10.1037/a0029312.
40. Roche AD, Vujaklija I, Amsüss S, Sturma A, Göbel P, Farina D, Aszmann OC. A structured rehabilitation protocol for improved multifunctional prosthetic control: a case study. J Visual Exp JoVE. 2015;105. https://doi.org/10.3791/52968
41. Segil JL, Huddle SA, Weir RF. Functional assessment of a myoelectric postural controller and multi-functional prosthetic hand by persons with trans-radial limb loss. IEEE Trans Neural Syst Rehabil Eng. 2017;25(6):618–27. https://doi.org/10.1109/TNSRE.2016.2586846.
42. Simon AM, Turner KL, Miller LA, Hargrove LJ, Kuiken TA, Pattern recognition and direct control home use of a multi-articulating hand prosthesis. In: 2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR), pp. 386–391; 2019. https://doi.org/10.1109/ICORR.2019.8779539
43. Waris A, Niazi IK, Jamil M, Englehart K, Jensen W, Kamavuako EN. Multiday evaluation of techniques for EMG-based classification of hand motions. IEEE J Biomed Health Inform. 2019;23(4):1526–34. https://doi.org/10.1109/JBHI.2018.2864335.

44. Ottobock.: 13E200 Electrode-Instructions for Use. 2021.
45. Rahimi A, Recht B, Random features for large-scale kernel machines. Adv Neural Informat Process Syst. 2008; 1177–1184.
46. Rahimi A, Recht B, Uniform approximation of functions with random bases. In: 2008 46th Annual Allerton Conference on Communication, Control, And Computing, pp. 555–561; 2008. https://doi.org/10.1109/ALLERTON.2008.4797607
47. Smith LH, Kuiken TA, Hargrove LJ, Linear regression using intramuscular EMG for simultaneous myoelectric control of a wrist and hand system. In: 2015 7th International IEEE/EMBS Conference on Neural Engineering (NER), pp. 619–622; 2015. https://doi.org/10.1109/NER.2015.7146699
48. Smith LH, Kuiken TA, Hargrove LJ. Evaluation of linear regression simultaneous myoelectric control using intramuscular EMG. IEEE Trans Biomed Eng. 2016;63(4):737–46. https://doi.org/10.1109/TBME.2015.2469741.
49. Hahne JM, Biebmann F, Jiang N, Rehbaum H, Farina D, Meinecke FC, Muller K-R, Parra LC. Linear and nonlinear regression techniques for simultaneous and proportional myoelectric control. IEEE Trans Neural Syst Rehabil Eng. 2014;22(2):269–79. https://doi.org/10.1109/TNSRE.2014.2305520.
50. SierraGonzález D, Castellini C, A realistic implementation of ultrasound imaging as a human–machine interface for upper-limb amputees. Front Neurorobot. 2013;7.
51. Hermansson L, Fisher A, Bernspång B, Eliasson A-C. Assessment of capacity for myoelectric control: a new rasch-built measure of prosthetic hand control. J Rehabil Med. 2004;1(1): 1–1. https://doi.org/10.1080/16501970410024280
52. Light CM, Chappell PH, Kyberd PJ. Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: normative data, reliability, and validity. Arch Phys Med Rehabil. 2002;83(6):776–83. https://doi.org/10.1053/apmr.2002.32737.
53. Kyberd P, Hussaini A, Maillet G. Characterisation of the clothespin relocation test as a functional assessment tool. J Rehabil Assist Technol Eng. 2018;5:2055668317750810. https://doi.org/10.1177/2055668317750810.
54. Bouwsema H, Kyberd PJ, Hill W, Van Der Sluis CK, Bongers RM. Determining skill level in myoelectric prosthesis use with multiple outcome measures. J Rehabil Res Dev. 2012;49(9):1331. https://doi.org/10.1682/JRRD.2011.09.0179.
55. Bunderson NE, Kuiken TA. Quantification of feature space changes with experience during electromyogram pattern recognition control. IEEE Trans Neural Syst Rehabil Eng. 2012;20(3):239–46. https://doi.org/10.1109/TNSRE.2011.2182525.
56. Nilsson N, Ortiz-Catalan M, Estimates of classification complexity for myoelectric pattern recognition. In: 2016 23rd International Conference on Pattern Recognition (ICPR), pp. 2682–2687. IEEE, Cancun (2016). https://doi.org/10.1109/ICPR.2016.7900040
57. Bolstad WM, Curran JM, Introduction to Bayesian Statistics. 2017.
58. Rasmussen CE, Williams CKI. Gaussian processes for machine learning. In: Mass: adaptive computation and machine learning. Cambridge: MIT Press; 2006.
59. Powell MA, Kaliki RR, Thakor NV. User training for pattern recognition-based myoelectric prostheses: improving phantom limb movement consistency and distinguishability. IEEE Trans Neural Syst Rehabil Eng. 2014;22(3):522–32. https://doi.org/10.1109/TNSRE.2013.2279737.
60. Nilsson N, Håkansson B, Ortiz-Catalan M. Classification complexity in myoelectric pattern recognition. J Neuroeng Rehabil. 2017;14(1):68. https://doi.org/10.1186/s12984-017-0283-5.
61. Atkins DJ, Sturma A. Principles of occupational and physical therapy in upper limb amputations. In: Aszmann OC, Farina D, editors. Bionic limb reconstruction. Cham: Springer International Publishing; 2021. p. 197–214.

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