DEVELOPMENT OF A MODULAR INTERFACE FOR MYOROBOTICS ACTUATOR CONTROL USING PREDICTED EMG MUSCLE ACTIVITY

MASTER THESIS

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NEUROSCIENTIFIC SYSTEM THEORY
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Problem description:
Many spinal cord injury survivors report that recovery of hand use would be the most desirable function to regain. Despite all the efforts in the field of brain-machine interface (BMI) during the last decades, the goal of achieving truly dexterous manipulation of objects remains elusive. By now, some recent research papers [1] have shown that recorded information from the primary motor cortex (M1) can be used to predict kinematic features of desired movement.
In addition, these signals can be used afterwards for real-time control of artificial muscles such as Myorobotics actuator.
The main objective of this thesis is to develop a driver interface for Myorobotics actuator control. The interface will use as input the predicted EMG muscle activity and force encoded in the primary motor cortex [2]. Moreover, the muscle-length, its time-course and the force measured by the Myorobotics actuator shall in turn be translated into realistic type Ia, Ib and II sensory signals.
The system shall be demonstrated using simple spinal reflex circuits, but shall as well be usable from large-scale brain simulations or live recordings of brain signals.

Tasks:
• Develop a modular driver interface that allows Myorobotics actuators to behave as muscle-like as possible, given their mechanical constraints.
• Use the predicted muscle activity and force from the motor cortex as an input to the driver interface for the Myorobotics actuator control.

Additional/Optional Tasks:
• Develop a two-stage decoder for EMG muscle activity and force prediction using recorded data from the motor cortex of the virtual brain model [3]
• Test and validate the model in a closed-loop scenario using the force measured by the Myorobotics actuator.

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Abstract

Muscle tissue is among the most versatile active materials as it provides contractile force over vast ranges and sizes. It is thus of interest to create artificial structures with comparable mechanical properties. Although the mechanical structure of the Myorobotics series elastic actuators closely resembles a macroscopic model of the skeletal muscles, crucial functional relationships are still lacking. Here we develop an interface for the Myorobotics single degree of freedom robotic arm with two artificial antagonist muscle units. First, the muscle activation is continuously decoded from the EMG signals of biceps and triceps brachii of a healthy subject. Afterwards, obtained activation values are propagated to the corresponding controllers that drive the robotic arm’s flexor and extensor muscle units. Importantly, the controllers encapsulate the Hill-type biological muscle model in order to guarantee biologically plausible activation and contraction dynamics of the artificial muscles. Finally, the muscles’ instantaneous length and the change of length are translated into realistic sensory fiber signals that can be used as a proprioceptive feedback for the closed-loop neuroscientific experiments. Experimental results demonstrate that the proposed methods for decoding muscle activation perform well in the real time scenario. Moreover, Myorobotics actuators exhibit force-length, force-velocity, and force-activation relationships in close resemblance of those observed within the biological muscles.
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Chapter 1

Introduction

Neurorobotics as a combined study of neuroscience, robotics, and artificial intelligence, has recently emerged, exploring the interaction between brain, body, and environment. Neural control research requires brain-like controllers as well as physical or simulated models that represent biological structures involved in the phenomena of interest. Therefore, advancements in this field are highly dependent on biological accuracy of such models. In particular, prosthetics and orthotics or brain-machine interfaces (BMIs), for instance, are widely adopting anthropomorphic structures due to their similarity with biology. However, a challenge of building a robot that matches behavioral and perceptual capabilities of the human body persists. Researches and engineers have been struggling to reach the same level of dexterity, flexibility, softness, and strength the human body exposes.

In pursuit of tackling this problem anthropomimetic robotics stands out as a key area. The main focus of the field lies in mimicking biological structures, such as human musculo-skeletal system. A number of actuators has been developed to imitate human morphology leveraging the power of elastic materials\[1\], pneumatics\[2\], hydraulics\[3\], or electric fields\[4\].

Tendon-driven musculo-skeletal robots present themselves as a suitable tool for closed-loop action-perception experiments. First, they offer light-weight end effectors, since the design allows high flexibility of actuator placement, which in its turn leads to the improved safety and compliance. Second, by virtue of the design tendon-driven systems allow building of flexible and scalable robots. Vivid examples of such advancements are a dexterous anthropomimetic hand \[5\] developed at the University of Washington or a full sized musculoskeletal humanoid Kenshiro \[6\] from the University of Tokyo.

Although tendon-driven actuators allow researchers to mimic mechanical structure of the human body quite well, replicating its dynamical properties poses yet another challenge on the way to biologically inspired neural control. At the very core of it lie functional principles of biological muscles, which serve as an interface between the central nervous system (CNS) and articulated body parts. As a first approximation, a classical macroscopic muscle model developed by Hill \[7\] is widely used to simulate
dynamical properties of multiple muscles simultaneously. In such a way force-length and force-velocity relationships of the biological muscle, as well as its proprioceptive feedback can be demonstrated and examined in the artificial setting.

In order to validate and assess how well tendon-driven robots are able to replicate the biomechanics of the human body, closed-loop experiments are required. Typically, electromyography (EMG) signals are used as inputs to estimate muscle’s contribution in movement generation.

1.1 Problem statement

The main focus of this thesis is to develop an interface for tendon-driven actuators that exerts the mechanical and dynamical properties of the human muscle. In this work we use a single degree of freedom anthropomorphic arm, built using the Myorobotics Toolkit, that consists of two muscle units (analogous to human biceps and triceps brachii).

Muscle activation is decoded from the surface EMG recording of a healthy human subject and then used as an input for the robot driver interface.

A macroscopic muscle model is incorporated into the actuator’s driver interface, in order to replicate natural muscle activation and contraction dynamics. The actuator’s muscle length, time-course, and force measured are translated into realistic sensory signals, that can be used as proprioceptive feedback for neural models.

The underlying theoretical background of the system components as well as a literature overview on the closely-related problems are given in Chapter 2. Chapter 3 presents a high-level overview of the system architecture and communication, while Chapter 4 examines in detail the implementation. Results and discussion are reported in Chapter 5 and Chapter 6 correspondingly, and finally the conclusions are drawn in Chapter 7.
Chapter 2

Theoretical Background

2.1 Myorobotics

2.1.1 Hardware Assembly

Myorobotics toolkit is a modular and reconfigurable system for developing musculoskeletal robotic platforms. It allows researchers to configure hardware setups tailored to the needs and requirements of individual experiments. The toolkit consists of design primitives that mimic the functions of their biological equivalents and can be configured into custom-made robots. The key hardware components are: bones, muscles, joints (with integrated perceptors), and ganglions. For the purpose of this thesis a robot was configured to emulate human elbow joint. Figure shows the Myorobotics system used, which consists of two MYO-muscles (matching elbow flexor and extensor muscle groups in the human arm), a single DoF MYO-joint, and a MYO-ganglion.

The MYO-bone is constructed from a solid T-slot aluminum profile with an end adapter on each side on the bone. Muscle or joints can be attached in any place along the profile. Thus, the structure provides low weight and high stiffness against torsion and bending.

MYO-joints are passive mechanical connector modules, complementing the MYO-bone to form the skeleton of the robot. To connect the lower and the upper arm (imitated using aforementioned aluminum profiles) hinge-type symmetrical joint was used. It provides one degree of freedom of rotation along an axis parallel to the joint end planes. The joint uses ball bearing for low friction operation and is equipped with an absolute angle sensor, comprising a magnet embedded in one of the axis and an electronic board with located inside the joint.

MYO-muscles (depicted in Fig. 2.2) are series elastic actuators that mimic skeletal muscle and thus they are the most notable distinction of Myorobotics w.r.t. conventional geared actuators. Instead of generating torques directly between two rigid links, MYO-muscle generates pulling force applied to the point of attachment on the bone. The body of MYO-muscle is made of 3D-printed polyamide, a 100
W DC motor (Maxon Motor EC series) is employed as an active force generator, that coils up a cable (equivalent of the biological tendon). The latter is connected through a set of pulleys to a spring-loaded guiding rod, that results into non-linear progressive spring behavior. An adjustable elastic element (a spring) connected in series with the contractile element (a motor). These are integrated, together with a sensor measuring deflection of the spring (hence the muscle generated force). In addition to compliance, the MYO-muscle design enables storage of elastic energy to achieve highly dynamic motion and leads to lower impact forces generated during unexpected collisions with the environment. Another peculiar property of the muscle units is the ability to only generate force under tension, not compression. Therefore, bidirectional actuation requires (similarly to human body) two antagonist muscle units.

MYO-ganglions are high speed communication and data-processing units, that collect available sensory feedback from muscle and joints. The current setup is based on the network communications protocol FlexRay (up to 10 MBit/s). One ganglion can control up to 4 MYO-muscles and pass information to the USB-FlexRay bridge that connects the robot with an external control system (a desktop PC in our case).


2.1. MYOROBOTICS

2.1.2 Software and Control

Figure 2.3 presents the timing behavior of this (partly) asynchronous communication system. At the highest level is the user application (UA). Typically, the cycle time of this control loop is in the tens of milliseconds range (e.g. 20 ms) and is set by the user. When a standard Ubuntu installation is used, the cycle time of the UA is not “hard real-time” and some variance on the timing is to be expected. In the UA, data from the Myorobot is read, such as motor velocity or joint angles, or set in the case of tendon force and motor position. Data is exchanged with the Myorobot via a thread that is hidden from the user by the FlexRayHardwareInterface and sometimes called USBI. It exchanges the data from the UA with the FlexRay2USB Adapter. The USBI also runs as a ”soft real-time” system with a nominal update rate of 500 Hz. In other words, data exchange between the UA (via the USBI) and the Myorobot is also limited to a minimum update rate of 500 Hz [10].

The next level of communication is realized with the USB-FlexRay bridge (UFR). Here, the USB data is exchanged with the ”hard real-time” FlexRay bus that forms the communication backbone of the Myorobot, allowing the exchange of data between the UFR and the MYO-Ganglions in a fully synchronous fashion at a rate of 1.0 kHz. The lowest level in the communication chain is formed by the linear-feedback controllers running on the MYO-Ganglions. The controllers run in a ”hard real-time” loop on the MYO-Ganglion and exchange data with the FlexRay bus and the motor driver boards. Currently, five motor control modes are possible:

- raw,
CHAPTER 2. THEORETICAL BACKGROUND

Figure 2.3: Cycle and communication times of the complete Myorobotics communication chain. Red arrows indicate that this communication parameter is user configurable [10].

- position (of the output motor shaft in rad)
- velocity (of the output motor shaft in rad/s)
- force (applied by the motor in N),
- torque (of a motor, in Nm).

In the raw mode, no feedback controller is enabled. Rather, the muscle is driven in an open-loop mode where the motor supply voltage can be varied between ±100%.

The remaining four control modes use the freely configurable linear-feedback control topology depicted in Figure 2.4.

Figure 2.4: The linear feedback controller topology: the controller is freely configurable within the flexrayusbinterface and runs on the MYO-ganglion [10].

Controllers run on the MYO-ganglion autonomously and are configured via the FlexRay-USB interface during the user-induced high level control system launch. Required parameters are specified in a YAML-file that contains the topological description of the robot, listing all ganglia, muscles associated with them including spring’s polynomial coefficients, motor’s control output limits, PID controller gains, and encoder ticks to physical units transformation ratios.
2.2. Biological Muscle and Its Modeling

Communication with the brushless-DC motor is implemented in the motor driver board that delivers the following feedback:

- motor shaft position which is sensed via an incremental encoder interface with differential inputs; the output shaft resolution is $r_{\text{output}} = 108544$ counts/rotation;
- spring displacement (indicates the tendon strain), sensed via magnetic strip and a hall-effect sensor with output resolution of $r_{\text{displacement}} = 66.6$ counts/mm;
- motor current is sensed via two shunt-resistors and is represented as integer in range $[0, 1023]$ with the smallest current that can be measured being 16.11 mA.

In order to improve the user experience we have developed a web-based graphical user interface (GUI). It presents an overview of the current state of the robot and offers convenient controllers for three of the aforementioned modes (position, velocity, and force). The plots (Figure 2.5a and 2.5b) allow to visually track individual muscle’s feedback described above, thus lead to better understanding of robot behavior during the setup and testing phase of the experiments. Moreover, intuitive GUI controllers (Figure 2.5c) help to adequately estimate robot’s reaction times and synergies between multiple muscle units. Lastly, emergency stop and initialization buttons liberate the end user from repetitive routines, and can prevent robot damage.

2.2 Biological Muscle and Its Modeling

2.2.1 Structure

A skeletal muscle consists of numerous tissue types that all contribute to muscle contraction, growth, and protection. Its outer layer that serves connective and protective function, encloses in itself multiple bundles of fibers. Each of them is a collection of equally long fibers connected in parallel, that consist of a set of homogeneous sarcomeres. A sarcomere is the smallest unit of the muscle that can contract. On a very basic level, it is built of actin and myosin filaments (proteins). Neural excitation triggers a change in the intracellular Calcium ion concentrations which leads to deformation of these filaments, and hence sliding of actin and myosin between each other, which causes muscle fiber contractions.

A set of muscle fibers is innervated by a motor neuron: together they form a motor unit. It is the smallest functional unit of the CNS that is associated with the muscle force generation. While motor neurons represent muscle inputs, sensory neurons deliver proprioceptive feedback back to the CNS. There are two types of proprioceptors: the muscle spindle and the Golgi tendon organ. The former encodes in spikes the change of length of the muscle, whereas the latter converts the instant muscle tension into spike train output [12].
(a) Gauges indicating current joint angles

(b) Online status plots for biceps

(c) Velocity control panel for four muscle units

Figure 2.5: Myorobotics GUI elements
2.2.2 Properties

Contraction dynamics is a key point in understanding of the muscle’s function. Determining fundamental principles underlying muscle contractions, however, is not a simple task. Experimental results continuously deliver discrepancies and inconsistencies, partially due to the unidentified structural components of the skeletal muscle. Therefore, in this work we will concentrate on well established fundamental properties, such as force-length, force-velocity, and force-activation relationships.

The force-length (F-L) relationship (Figure 2.7a) describes the dependence of the steady-state isometric force of a muscle (or fiber, or sarcomere) as a function of its length. It is characterized by a positive slope (i.e. force is getting greater as length increases) at short lengths, a zero slope (the so-called plateau region) at intermediate lengths, and a negative slope (i.e. force decreases with increasing lengths) at long muscle lengths. The length corresponding to the plateau region is called muscle fiber optimal length (or resting length) and results into the peak force that muscle is able to generate.

The force-velocity (F-V) relationship is the observation that muscle force and contraction velocity are inversely related. It has been experimentally shown that as muscle force increases, the rate of muscle shortening decreases in a hyperbolic fashion as shown Figure 2.7(c). The F-V relation has proven its essential value in predicting force generated by the shortening muscle fibers.

Another fundamental factor affecting muscle tension is the level of neural excitation.

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1Due to the homogeneous nature of sarcomere arrangement, their function and excitation patterns within a motor unit, the properties of the latter can be represented as a scaled version of those a single sarcomere possesses. Furthermore, taking into account homogeneity between motor units of the same type, muscle tissue properties are equivalent to any of its fibers or sarcomeres that form it. Thus, when describing properties of a muscle, it is assumed they correspond to a scaled version of properties of their smaller building blocks.

2For the purpose of this study, the effects of spike rate encoding and motor unit recruitment are combined together under the notion of muscle activation.
CHAPTER 2. THEORETICAL BACKGROUND

(a) Isometric force-length relationship for fully activated and passive muscle

(b) Isometric force-length relationship for activated \((q = 0.5)\) and passive muscle

(c) Force-velocity relationship of a fully activated muscle

Figure 2.7: Properties of a biological muscle \[13\].
The degree of activation has been shown to alter the F-V relation: less intense neural excitation leads to less force generated as illustrated in Figure 2.7a (full muscle activation) and Figure 2.7b (50% muscle activation).

It is worth mentioning that muscle activation history has been proven to cause both fatigue and enhancement, that affect the muscle tension. In this study, these properties are not taken into account, and therefore are not explained in this section.

2.2.3 Model

In order to discover the underlying mechanism of muscle functions, interpret experimental results, as well as investigate biological movement generation, multiple muscle models have been introduced. There exists no universal solution in skeletal muscle modeling, but rather each problem requires to consider various levels of detail and scales. Two widely adopted muscle models are those developed by Hill [7] and Huxley [14], respectively revealing muscle structure on the macro- and microscopic level. While Huxley’s model is capable of describing muscle’s behavior on the subcellular level (interaction between actin and myosin filaments), it is computationally expensive and involves more than 30 parameters coupled in several differential equations. Since intricate internal details of the muscle fibers were not the main focus of this study, we employ a Hill-type model to investigate the high level functional characteristics of skeletal muscles. It is a purely mechanical model, built from a systems engineering perspective, that aims to reproduce overall behavior of the muscle within accepted level of deviation from physiology.

In essence, as described by Hill, the model consists of three main parts: a contractile element (CE), a series elastic element (SEE), and a parallel elastic element (PEE). Figure 2.8 demonstrates the canonical arrangement of the aforementioned elements. Here, CE is the source of active energy (equivalent of actin and myosin filaments inside the sarcomere). Its main function is contraction when the muscle is stimulated. Passive behavior of the muscle (connective tissues) is modelled by the parallel...
elastic element, that influences the F-L relationship when the muscle is stretched and the CE is not activated. Finally, the SEE models the tendon’s behavior, i.e. elastic storage of energy. Three elements combined fulfill the force equilibrium:

\[ F_{SEE} = F_{CE} + F_{PEE} \]

The kinematic relations of the elements are:

\[ l_{PEE} = l_{CE} \]

\[ l_{SEE} + l_{CE} = l_m \]

Force generated by each muscle \( F_m \) is dependent on muscle’s current length \( l_m \), velocity \( \dot{l}_m \), activation level \( q \), and a number of internal parameters. Thus,

\[ F_m = f(q, l_m, \dot{l}_m, params) \]

The detailed description of the model is formulated in the implementation section. There are three primary relationships that are important to emulate the behavior of muscle. These are the tension-length, force-velocity, and stimulus-tension curves mentioned before. The results chapter presents an assessment on how well the Hill-type muscle model replicates these characteristics.

### 2.3 Electromyography

An electromyography (EMG) signal is a biomedical signal that measures electrical activity produced in a muscle during its contractions. It originates from the neural stimulation that causes muscle contraction, and therefore is intuitively used in our work as a driver for the muscle model and hence, the robot. EMG signals capture electric potentials of multiple motor units. To instantiate a contraction, a neuron generates a small electrical potential on the surface of the muscle fiber. The electrical signal from a single motor unit is a summation of responses of every muscle fiber within it and is called motor unit action potential (MUAP). In order to sustain contraction for a prolonged period of time, a motor unit is repeatedly stimulated resulting into a so-called MUAP train. Since muscle consists of multiple muscle fiber bundles, a superposition of fibers’ MUAP trains firing simultaneously is what sEMG is measuring (Figure 2.9).

Typically, EMG signal amplitude ranges from 0 to 10 mV (peak-to-peak). The usable energy of the signal lies in the 0-300 Hz frequency range, with dominant energy contained in a 50-150 Hz range [16]. A biosignal amplifier is used to acquire EMG signals. It increases the power of the signal and eliminates noise. The signal is however influenced by numerous factors, such as muscle and skin physiological properties, as well as characteristics of the acquisition toolset and recording conditions. Most importantly, electrical conductivity
of skin is influenced by various factors, such as tissue type, thickness, or temperature to name a few. Therefore, the EMG signal can greatly vary in cross-subject recordings. This prohibits a direct quantitative comparison. In addition, electrode placement plays an important role is signal collection and may significantly distort it if done incorrectly. Furthermore, EMG signal collection is likely to be distorted by the ambient noise, that originates from sources of electromagnetic radiation (electrical power wires, for example). In addition, contact of electrode and the skin as well as shifting of the cables between the electrode and amplifier represent additional noise source, that contaminates the signal. Finally, the quasi-random nature of the firing of the motor units contributes to an inherent instability of the signal and therefore is considered as an unwanted noise. Hence, a number of filtering techniques has to be applied for denoising raw EMG signal.

2.4 Related Work

In order to solve the problem stated in Section 1.1 three components are required: a physical tendon-driven robot representing a human limb, a muscle model, and biological motor system inputs obtained from the human subject. To our knowledge, a system incorporating all of the aforementioned components together has not been demonstrated yet. However, when taken individually these areas of research are well studied and introduced in literature in great detail. In addition, the combination of two components (a muscle model and a virtual robotic limb [17] or EMG-driven traditional gear-actuated robot [18]) has been successfully demonstrated in recent scientific publications. Muscle models are commonly used to analyze body movements and predict passive and active muscle forces. Haeufle et al. [19, 20] developed a Hill-based computational model of the macroscopic mechanical structure and function for the biological muscle. The model was tested for both software simulation and hardware setup. While the numerical simulation was shown to successfully replicate rapid human-
like elbow joint movements using flexor and extensor muscles, the hardware setup was designed with a single muscle unit and subject to multiple limitations and simplifications, such as neglected activation dynamics, force-length relation, or contraction history effects. Besides, for the hardware experiment two direct current (DC) brushless motors were used for a single muscle-tendon unit, which negatively affects the scalability of the presented system.

Another neuromuscular application was demonstrated by Cavallaro et al. [18] who developed a neurally controlled powered exoskeleton arm that was using a Hill-type muscle model to predict joint torque based on the physiological muscle activation levels and joint kinematics. Their model consisted of seven muscles and sub-muscle groups that were used to build a three-dimensional anatomical representation of the upper limb. Initially, Hill’s model internal parameters preserved close ties with the physiological parameters of muscles, and were subsequently optimized using a large dataset of surface EMG recordings from 28 muscles during flexion/extension movements under different loads. While demonstrating good performance (4.2 ± 0.97 Nm root mean square error for elbow joint torque estimation), the system showed the necessity of parameter fine-tuning for each subject individually in order to adapt to differences in muscle and skin composition between subjects, as well as data collection with a high number of electrodes used for a single joint to capture the movements in high resolution accordingly.

Identical trends are shown in the studies of Lloyd [21] and Manal [17] in the experiments with a real-time EMG-driven virtual arm and estimating muscle forces and knee joint moments, where Hill-based muscle modeling and nonlinear optimization methods are applied as well. They too require an individual parameter optimization for calibration purposes and a high number of EMG channels recorded (7 muscles for elbow flexion/extension).

Another limitation presented in Manal’s study is that the subject performed only isometric contractions in order to control dynamic movements of the virtual arm. Additionally, due to ethical and methodological considerations measurement of human muscle forces in vivo is not used in scientific experiments, so that only inverse dynamics and kinematics calculations can be used to calibrate and validate the models, which raises a question regarding the correspondence between actual and estimated muscle forces. Lastly, it could be argued that the physiological correctness of the model does not play a big role for accurate muscle forces estimation, since the approach narrows down to a trivial curve fitting exercise.

The most studies concentrate on estimating muscle forces directly from the surface electromyography signals. In essence, this approach consists of two components: feature extraction and a regression/classification model. The most frequently used feature extraction methods in the study of EMG signals are:

- mean absolute value [22];
- mean frequency [23];
2.4. RELATED WORK

- root mean square [23];
- continuous [24] and discrete wavelet transform [25];
- short-time Fourier transform [26].

Aforementioned features are typically fed into an artificial neural network (ANN) [25] or polynomial regression model [24], that yield estimated force. Similarly to Hill-type muscle modeling, the direct force estimation approach enforces training the models for each individual separately, due to high cross-subject variability of the EMG signal.

In the study of Bai et al. [27], for example, CWT features in combination with an ANN is used to estimate muscle force during dynamic muscle contractions. The EMG signals from the 4 muscles involved in knee flexion/extension of 14 subjects were recorded for this experiments. The presented method is able to estimate muscle forces with relative error of 17.01% (average across all subjects). However, measured forces are limited to 60-80% of the maximum force. Figure 2.10 shows force estimation results during knee flexion and extension.
Chapter 3
System Design

The developed system is divided into three main parts: data acquisition, data processing, and robot actuation. Figure 3.1 illustrates general system architecture, including main modules and data flow protocols used. The biosignal amplifier is connected via USB port to the Windows 7 machine with a module, that resends incoming data as UDP packets on the local network. The rest of the system runs under Ubuntu 16.06. Here, the EMG processing module picks up the signal and applies a number of basic filters in order to remove various inherent artifacts. After denoising, the data is piped over the ROS network to the Activation Decoder. This component extracts required features from the EMG, decodes muscle activation, and passes it further to the Hill Muscle Model. The latter receives two inputs over the ROS network: activation level from the EMG processing module and the current state of the robot (muscle length and velocity) from the Myorobotics Interface module. Thus, based on the incoming data Hill muscle model derives the force and propagates it to the Myorobotics Driver, that in its turn triggers a procedural call to apply desired tension to the motor. In addition, Myorobotics Driver serves a mediator function between the FlexRayUSB interface and the web-based Myorobotics GUI, so that it

1) transmits information about the robot state (received from the FlexRayUSB interface) to be displayed in the GUI,

2) invokes ROS services (required to control the robot) that are connected to GUI elements.

The key advantage of the developed system is the modularity. It ensures that each component is self-sufficient and easily-extendable or replaced. In such a way, the Data Acquisition module is not tailored to one specific type of the amplifier. By the virtue of using the Lab Streaming Layer (LSL) library, the hardware can be easily exchanged, while the module’s input/output remain the same. Similarly, introduced functionality is not limited hardware-wise to only one specific robot setup. As Myorobotics toolkit allows for various configuration changes, system is meant
Figure 3.1: System architecture
to be highly adaptable to reflect those. Furthermore, software components, such as EMG Processing or Hill Muscle Model modules, leave a certain amount of freedom in choosing exact implementation to the developer. For instance, while inputs and outputs of the Hill Muscle model will remain unchanged, the internal structure can be arbitrarily modified to exhibit desired properties. Finally, system architecture allows to decouple components and independently use their functionality. Thus, Myorobotics Interface and GUI combined present an exhaustive tool for conducting both robotics and neuroscientific experiments. Equivalently, Hill muscle model delivers self-sufficient functionality to simulate a biological muscle.

At the first sight, system’s language variety may seem to be its drawback or limitation. However, each module’s language was chosen to serve its purpose best:

- Python was chosen for data acquisition mainly due to its low-cost configuration effort and extensive support libraries;
- data processing part was mainly implemented using MATLAB considering a vast amount of built-in algorithms;
- apart from being a primary ROS language, C++ ensured the necessary speed and efficiency for the robot communication;
- JavaScript served as a cross-platform and user-friendly data visualization tool, and thus was picked to implement the graphical user interface.

**Communication standard.** A smooth data exchange between multilingual software parts of the system is guaranteed by leveraging the Robotic Operating System (ROS) network infrastructure. There are two basic concepts of data transmission in ROS: messages and services. A ROS message is a data structure, comprising typed fields. It is routed via a transport system with publish/subscribe semantics. A process (i.e. ROS node) publishes a message under a given topic (unique identifier). A module that is interested in receiving the contents of specific message, subscribes to an appropriate topic. Publishers and subscribers are decoupled and are not aware of each other’s existence. There could be multiple concurrent publishers and subscribers on the same topic (even within one node). ROS services, on the other hand, provide request/reply interactions. They can be seen as remote procedural calls. A providing node offers a service under a certain name, whereas a client sends a request message (using the appropriate name), awaiting for response [28]. Myorobotics Driver node’s main purpose is to isolate FlexRayUSB interface from interaction with external modules and to provide an access point containing Myorobot state information and controls. Thus, the Myorobotics Driver node offers the following functionality:

- ROS topics:
  - /myo/muscles/{name}/sensors
EMG Processing node advertises /bio/muscles/{name}/activation topic, which is picked up by the Hill Muscle Model, that in its turn sends sensory feedback of the muscle under the ROS topic /myo/muscles/{name}/afferents/discharge/rate. Remaining system modules either make use of information and function calls provided by aforementioned services and topics, or advertise their own data using these topics.
Chapter 4

Implementation

4.1 EMG Analysis

4.1.1 Experimental Setup

This thesis concerns itself with mimicking the behavior of the human elbow joint using the Myorobotics arm with two muscle units: elbow flexor and extensor. Therefore, the main purpose of the experiment was to capture electromyography activity of biceps brachii and triceps brachii of a healthy subject during isometric contractions. In order to eliminate the inconsistencies (coming from improper calibration of measuring devices, for instance) EMG signal was recorded in the state of force equilibrium between the human and robotic arm during isometric contractions. The experiment consists of the following steps:

1. Skin preparation. Subject’s skin around target electrode placement sites was wiped using an alcohol swab in order to remove surface oil and other contaminants.

2. Electrodes placement. Both muscles used a common reference electrode placed on the bony non-muscular part of the arm - on the surface of triquetral bone (wrist). Biceps and triceps were then recorded using two electrodes each (required for bipolar derivation): first electrode was placed in the middle of target muscle body and second - towards the end of it. The distance between two electrodes exceeded 2 cm. Importantly, the electrodes were not placed near or on the tendon of the muscle, as the muscle fibers there become thinner and fewer in number and the area is susceptible to signal crosstalk [16]. The electrode cables were arranged in such a manner, that they undergo minimal displacement during active parts of the experiment. The sEMG signals were recorded using self-adhesive liquid-gel Ag/AgCl surface electrodes of 35 mm in diameter (Kendall H135SG). Data was sampled at 600 Hz with the g.USBamp - USB biosignal amplifier from g.tec medical engineering [20] (Figure 4.1a).
3. **Calibration.** The most common method of the EMG signal normalization uses activity recorded during the maximum voluntary isometric contraction (MVIC) \[30\]. It is a reference test that produces the maximum contraction in the muscle of interest. For this purpose, subject’s arm was fixed, so that the elbow joint was immobilized at 90° position. In order to obtain biceps MVIC subject was instructed to try to flex his lower arm in the direction of the shoulder with maximum effort, whereas for triceps MVIC - extend the arm in the hip direction with maximum force. Importantly, experiment participant was advised to keep usual respiration patterns, since they may cause significant value changes as shown in \[31\]. Each MVIC trial duration was 1-3 seconds. For repeatability purposes at least three repetitions of each test were conducted for each muscle with minimum 60 seconds pause in between to reduce any fatigue effects.

4. **Rest.** A break of 3 minutes separates the calibration phase and the actual trial, again to minimize fatigue influence on the data.

5. **Wrestling.** During this part of experiment (Figure 4.1b), the Myoarm first tries to move in the direction towards the subject. Subject is instructed to keep force equilibrium with the robot (at robot’s optimal muscle length position) using the minimum possible effort. In this setting robot’s biceps and human triceps are activated. The same movement was repeated for 10 times, with 4 seconds holding force period and 3 seconds of relaxation in between trials (for both subject’s and robot’s muscles). Equivalent procedure was conducted with robot moving outwards the subject, that involved activation of the human biceps and robot’s triceps.

### 4.1.2 Data Processing

EMG data was treated for each muscle separately. After the raw signals were obtained from the amplifier (two electrodes per muscle), bipolar derivation was performed:

\[
x(t) = x(p_1, t) - x(p_2, t)
\]

where \(p_1\) and \(p_2\) are the locations of electrodes, \(x(t)\) is the signal used for further processing. Next, band-pass 4\textsuperscript{th} order Butterworth filter (10-300 Hz) was applied to the signal cutting off both low and high frequencies, in such a way excluding environmental noise. Additionally, the data was filtered using 50 Hz notch filter to remove power line interference. Data, acquired during both calibration and active phase of the experiment, was pre-processed in the same way.

For the normalization purposes, electromyography signal during the maximum voluntary isometric contraction was used, in order to guarantee reliable reference values for different muscles and across trials. The normalization value was obtained by calculating the linear envelope of the signal and taking its maximum (\(x_{\text{max}}\)).
4.1. EMG ANALYSIS

(a) Biosignal amplifier g.USBamp and web-based GUI for real time visualization of the signal

(b) Wrestling phase of the experiment

Figure 4.1: Data collection

4.2 shows EMG signal during calibration phase (in blue) and its linear envelope (in red). For all repetitions of the test, sEMG was normalized against the MVIC maximum:

\[ x(t) = \frac{x(t)}{x_{\text{max}}} \]

In addition, we applied data standardization to remove potential biases between two channels signal:

\[ x'(t) = \frac{x(t) - \bar{x}}{\sigma} \]

where \( \bar{x} \) is signal’s mean value, \( \sigma \) is its standard deviation, \( x'(t) \) is the standardized signal.

Figure 4.3 shows frequency domain of an arbitrary sample of subject’s EMG signal after the pre-processing procedure, which is summarized in Figure 4.4.

**Feature extraction.** The purpose of the feature extraction is to obtain a representation of the original signal, that contains necessary information of interest. Methods used for feature extraction are tailored to specific application and objective. In this study, we analyzed and compared performance of the root mean square (RMS) and discrete wavelet transform (DWT) as feature extraction techniques.

**RMS** is a linear envelope of a signal. For each data point \( x(k) \) a window of \([x(k - W), x(k + W)]\) is considered so the resulting value at \( x(k) \) is averaged w.r.t. the
Figure 4.2: Maximum voluntary isometric contraction recording with the linear envelope of the signal shown in red.

Figure 4.3: Rectified EMG signal recorded from biceps brachii during isometric contractions presented in the frequency domain.

Figure 4.4: Signal preprocessing steps

- Raw EMG
- Band-pass filter (10-300 Hz)
- Notch filter (50 Hz)
- MVIC Normalization
- Normalization to zero mean and constant variance
4.1. EMG ANALYSIS

neighboring points, i.e. "smoothed" in the following manner:

$$\hat{x}(t) = \sqrt{\frac{1}{2W} \sum_{k=t-W}^{t+W} |x(k)|^2}$$

where $\hat{x}(t)$ is the signal’s RMS.

**Wavelet transform** is a suitable technique for analyzing non-stationary signal. It delivers high-resolution time-frequency features. DWT is characterized by an increased adaptability to specific application when compared to short-time Fourier transform or using maximum absolute value as features for instance, as well as a low computational power ($O(N)$ time complexity).

Discrete wavelet transform uses filter banks for the construction of the multiresolutional time-frequency plane. A filter bank is a set of low- and high-pass filters that separate signal into equal-width frequency subbands, which are respectively called approximations $A$ and details $D$ of the signal $x(t)$. Each subsequent level of DWT takes into account only approximation components of the previous level. Since each time half of the frequencies of the signal are removed, half of the samples can be discarded according to the Nyquist’s rule. Thus, filters’ outputs are downsampled by the factor of 2. Figure 4.5 demonstrates the flow of the four level filter bank. As a result of signal decomposition, details components from all levels and approximation component only of the last one are obtained.

Wavelet transform is defined by a wavelet mother function $\psi(x)$

$$\psi_{j,k}(x) = \frac{1}{2^j} \psi\left(\frac{x - 2^j k}{2^j}\right)$$

and a scaling function $\phi(x)$ associated with it. The filters $g$ and $h$ (used in filter

![Figure 4.5: Discrete wavelet transform on level 4](image-url)
bank DWT implementation) characterize interaction of $\phi$ and $\psi$ functions:

$$g[k] = \frac{1}{\sqrt{2}} \langle \psi(x/2), \phi(x-k) \rangle$$

$$h[k] = \frac{1}{\sqrt{2}} \langle \phi(x/2), \phi(x-k) \rangle$$

The level of signal decomposition and wavelet mother function play an important role and affect greatly the quality of signal representation. There is no standardized procedure for selection of the aforementioned parameters, which are highly dependent on the application. Based on the comparative analysis presented in [32] and empirical results, $db2$ mother wavelet function from Daubechies family was chosen, due to its similarity to the shape of the motor unit potentials (that comprise EMG signal) as well as the best signal-to-noise ratio when compared to other wavelet function families (symlet, coiflet, biorthogonal). For the given application, the wavelet transform was empirically proven to deliver best result when the fourth level of decomposition was used. These coefficients correspond to signal’s frequency range of 20-70 Hz (where the most of signal power lies according to Figure 4.3, which justifies our choice of level and coefficients.

Based on the results presented in [26], maximum absolute value (MAV) of the detail coefficients of the last level are used as a feature, which yield a sufficient representation ($r$) for the signal in low dimension:

$$r = \max(|d_1|, |d_2|, ..., |d_n|)$$

where $d_j$, $j = 1, n$ are the wavelet detail coefficients on the level 4.

Discrete wavelet transform was performed using MATLAB Wavelet Toolbox on a preprocessed EMG signal divided into windows of 250 ms. As the raw features yielded by the time-frequency analysis are relatively noisy and activation-related information correlates with lower frequencies, a low-pass filter with the cut-off frequency of 10 Hz was applied to the feature data, before proceeding to the activation decoding phase. Since the features are calculated for a windowed version of the EMG signal, the activation data was downsampled by taking its mean value in each window.

### 4.1.3 Activation Decoding

Considering the nature of EMG origin, the relationship between the level of activation and the recorded signal of a muscle is linear. However, experimental data does not show this property due to the following factors:

- empirically it is very difficult to achieve a truly isometric contraction under different levels of activation;
4.1. EMG ANALYSIS

Figure 4.6: ANN schematics with linear envelope of the signal as input

- in vivo observation of a single muscle in isolation is cumbersome, due to synergy between different muscles;

- muscle fibers composition affects the relationship, i.e. faster twitch muscle fibers may cause exponential growth of muscle activation.

Thus, in this study we leverage mathematical models that are able to capture empirical non-linear relationship between muscle activation and electromyography: an artificial neural network (ANN) and a polynomial estimator. Muscle activation data was obtained through scaling of forces recorded by Myorobotics actuators (during the equilibrium).

**Artificial neural network.** In order to obtain an EMG-to-activation model, a feed-forward neural network was implemented in MATLAB and trained using the data obtained from 5 trials (lasting 160 s each). Network consists of a single neuron on input and output layers and three hidden layers with six neurons each. *tansig* (hyperbolic tangent sigmoid) transfer function was used in the hidden layers, and *purelin* (linear) on the input and output ones. ANN was trained using scaled conjugate gradient backpropagation with GPU parallelization. Data was randomly divided in the following manner:

- training set: 70%
- validation set: 15%
- testing set: 15%

A similar configuration ANN was used for training with root mean square feature, with only difference being the dimensionality of the input layer. Network’s architecture is presented in Figure 4.6.

**Polynomial estimator.** In another approach to model EMG-activation relationship, we exploited a second-degree polynomial in the following form:

\[ q_e = c_1 r^2 + c_2 r + c_3 \]

where \( q_e \) is the estimated activation level, \( r \) is the representation of the signal, and \( c_i, \; i = 1, 3 \) are the parameters of the estimator. The latter were optimized by
using non-linear least squares (LS) fitting (MATLAB Optimization Toolbox) with objective function:

$$
\text{min} \| F(t) \|_2^2 = \text{min}(f(t_1)^2 + f(t_2)^2 + \ldots + f(t_n)^2)
$$

$$
f(t) = q_e(t) - q_m(t)
$$

where $q_e$ and $q_m$ are estimated and measured activation respectively and $n$ is the size of training dataset. Configuration parameters of the solver are presented in Figure 4.1.

Here, similarly to ANN approach, 80% of collected data was used for optimization and the rest 20% to evaluate the performance of the estimator.

The flowchart of the signal processing procedure is shown in Fig. 4.7.
4.2. MYOROBOTICS HILL-TYPE DRIVER INTERFACE

This part of the thesis aims to present implementation details of the Myorobotics driver interface that ensures biologically plausible behavior of artificial muscle units. Although by design Myorobotics actuators strive to replicate dynamical and mechanical macroscopic properties of a skeletal muscle, in practice the inconsistencies regarding both of these aspects are still present. Thus, we employ and adapt a Hill-type muscle model to complement missing features. As described before in section 2.2 key model’s components are:

- contractile element (CE),
- series elastic element (SEE),
- parallel elastic element (PEE).

Contractile element represents the active fiber bundles in the muscle. First, its force depends on the current length, which is represented by the following relationship

\[
F_{\text{isom}} = \exp \left\{ - \frac{l_{\text{CE}}/l_{\text{CE, opt}} - 1}{\Delta W} \nu_{\text{CE}} \right\}
\]

where is \( l_{\text{CE, opt}} \) is optimal muscle length, \( l_{\text{CE}} \) is current length of CE, \( \Delta W \) and \( \nu_{\text{CE}} \) are characteristics of a normalized bell curve in the respective limb (width and exponent correspondingly). Second, the \( F_{\text{CE}} \) depends of the current velocity of muscle contraction \( (\dot{l}_{\text{CE}}) \):

\[
F_{\text{CE}} = F_{\text{max}} \left( \frac{qF_{\text{isom}} + A}{l_{\text{CE}}} - A \right) \left( 1 - \frac{l_{\text{CE}}}{Bl_{\text{CE, opt}}} \right)
\]

with \( F_{\text{max}} \) being the maximum isometric force, \( A \) and \( B \) - Hill parameters, that vary

<table>
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<th>Parameter</th>
<th>Value</th>
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<td>Maximum number of iterations allowed</td>
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<td>Termination tolerance on the first-order optimality</td>
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</tr>
<tr>
<td>Termination tolerance on step size</td>
<td>1e-6</td>
</tr>
</tbody>
</table>

Table 4.1: Least-squares solver configuration
subjected to the length $l_{CE}$ and activation $q$ in the following manner \cite{20}:

$$A(l_{CE}, q) = \begin{cases} 
  A_0 F_{isom} \frac{1 + 3q}{4} & \text{if } l_{CE} \geq l_{CE,opt} \\
  A_0 \frac{1 + 3q}{4} & \text{else}
\end{cases}$$

$$B(q) = B_0 \frac{3 + 4q}{7}$$

Importantly, force of the contractile element $F_{CE}$ developed during eccentric contractions (muscle fibers lengthening) when calculated with Hill parameters $A$ and $B$ using equations presented above does not coincide with the experimental results. Therefore, the formulas have to be adjusted, using two additional parameters: $F_e$, which is a factor by which the force can exceed $F_{isom}$, and $S_e$ - relation between F-V slopes at $v_{CE} = 0$. Thus, the values of $A$ and $B$ to be used to during eccentric contractions are \cite{4}

$$A_e = -F_e q F_{isom}$$

$$B_e = \frac{B(1 - F_e)}{S_e \left( 1 + \frac{A}{q F_{isom}} \right)}$$

Parallel elastic element (PEE) behavior is described by below presented equations:

$$F_{PEE}(l_{CE}) = \begin{cases} 
  K_{PEE} (l_{CE} - l_{PEE,0})^{\nu_{PEE}} & \text{if } l_{CE} \geq l_{PEE,0} \\
  0 & \text{else}
\end{cases}$$

with two free parameters $K_{PEE}$ and $\nu_{PEE}$.

In the implementation we used biologically plausible parameters for major elbow flexor and extensor muscles based on \cite{33, 34, 35}, with only exceptions for $F_{max}$ and $l_{CE,opt}$ that were defined by the Myorobot configuration. Hill muscle model parameters and their values are listed in Appendix A.

Figure 4.8 shows the minimal mechanical structure of the system, that allows to replicate dynamical properties of the biological muscle, in comparison with the mechanical structure of the Myorobotics actuator. This representation of the MYO-muscle evidently demonstrates lack of the PEE, which is responsible for passive properties of a muscle. Thus, a virtual PEE was integrated into the Myorobotics controller in order to compensate for mechanically missing component.

The Myorobotics controller calculates force of the musculo-tendon complex $F_{MTC}$ using received online data from a physical robot. The general flow of the data between the Myorobotics actuator and the implemented Hill-type muscle model is depicted in Figure 4.9, whereas the detailed steps of the algorithm are shown below:

1. Initialize the robot.

\footnote{Full derivation is shown in \cite{20}.}
2. Read in activation level
3. Read in the current $l_{CE}$, $\dot{l}_{CE}$, $l_{SEE}$ from the robot
4. Calculate $l_{PEE}$
5. Publish ROS messages containing sensory fibers discharge rates:
   - The discharge rate of the primary afferent is proportional to the length of the series elastic element: $S_{Ia} \sim l_{SEE}$
   - Secondary afferent fire in correspondence with the contractile element: $S_{II} \sim l_{PEE}$
6. Indicate descending (muscle shortening) or ascending (lengthening) branch
7. Calculate $F_{isom}$
8. Calculate $F_{PEE}$
9. Derive Hill parameters $A$ and $B$ (dependent on the type of contraction)
10. Calculate $F_{CE}$ and $F_{MTC} = F_{CE} + F_{PEE}$
11. Call a corresponding ROS service for the motor to hold target force $F_{MTC}$
12. Repeat from Step 2.
Figure 4.9: Data exchange between Hill Muscle Model and Myorobotics Muscle components
Chapter 5

Results

5.1 Activation Estimators

Muscle activity level decoding was implemented using three approaches:

- regression with a 2-order polynomial using as features level 4 detail coefficients of the DWT applied to EMG signal;

- an artificial neural network using as features level 4 detail coefficients of the DWT applied to EMG signal;

- an ANN using as features linear envelope (RMS) of the EMG signal

Plots below present a comparative performance overview of the estimators based on the root mean square error (RMSE) and the Pearson correlation coefficient (PCC), defined as follows:

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \]

\[ PCC = \frac{\sum_{i=1}^{n} (y_i - \bar{y})(\hat{y}_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2} \sqrt{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}} \]

with \( y_i \) as measured values, \( \hat{y}_i \) as predicted values, \( \bar{y} \) and \( \bar{y} \) are corresponding means, and \( n \) being a number of samples in dataset.
Figure 5.1: Pearson correlation coefficient between measured and estimated activation levels

All three approaches demonstrate (Figure 5.1) high correlation coefficients (close to 1) between the measured and estimated outputs, proving a strong positive linear relationship between them. Importantly, a polynomial with DWT features shows far better PCC performance when compared to other models.

Figure 5.2: Root mean square error during activity level estimation
RMSE (depicted on Figure 5.2) shows low average forecasting error for the implemented estimators. Here, the model with RMS as input shows a better absolute fit, while using DWT derived features decreases estimator’s accuracy. RMSE is inherently sensitive to the occasional large errors, thus discrete wavelet transform features can deal with outliers worse than RMS.

Figure 5.3 and Figure 5.4 give an insight on the course of training of the artificial neural network with different features. Evidently, RMS input led to the longer
convergence time (due to higher dimensionality of inputs). Training both networks however was stopped due to absent improvement of accuracy on validation datasets over the consequent six epochs, hence finishing the training with accuracy of 0.0133 (DWT input) and 0.0132 (RMS input).

Figure 5.5: Normalized residual plot for least squares optimization of the 2-order polynomial

Residuals (difference between the actual and estimated value, Figure 5.5) vary randomly around zero with about the same spread throughout the plot, they are clustered around low y-axis values, proving the model to be a good fit. Nevertheless, the residual plot shows a clear pattern that much more often prediction value was too low, rather than high.

Figure 5.6 shows predictions of activation level along with its actual values. As suggested by evaluation statistics, estimators generally perform badly when the measured values are high.

To sum up, the polynomial model using DWT features shows better performance on average, while the ANN with the RMS on input can better deal with the outliers (activation levels rarely occurring in the training dataset). Artificial neural network’s architecture allows to capture the relationship between the EMG signal representation and the activation level in more detail due to a higher number of free parameters (weights and biases on each layer) when compared to the polynomial with a distinctly lower number of those. Nevertheless, all three of the proposed estimators are suitable for the real time activation decoding, since they operate on the small window size (250 ms) of the EMG data and are computationally inexpensive.
5.1. ACTIVATION ESTIMATORS

Figure 5.6: Comparison between estimated and measured activation
5.2 Myorobotics Actuator as Biological Muscle

In this work, we focused on replicating the following core properties of the biological muscle fibers:

- force-velocity relationship,
- force-length relationship,
- force-activation relationship,
- proprioceptive feedback.

Figure 5.7 demonstrates data collected from the Hill-type Myorobotics controller under various loads. Here, the force-velocity line curvature resembles hyperbola with minor deviations inherent to hardware experiments caused by additional friction (motors, bearings) in the setup.

Dependency of muscle tension and length is depicted in Figure 5.8. While the maximum active force (represented by CE) is achieved at the optimal length of the contractile element, it gradually decays as the length deviates from its optimum. Parallel elastic element\footnote{In our implementation resting length of the parallel elastic element is set to 0.9l_{CE, opt}} models passive behavior of the muscle, i.e. when the muscle is not activated (q = 0) but stretched, total force exerted by the muscle will be positive, increasing with length.
5.2. MYOROBOTICS ACTUATOR AS BIOLOGICAL MUSCLE

Equivalently to the biological muscle fibers, tension-activation curve is scaled according to level of neural stimulation. Thus, with activation level of 70% length-force line curvature remains, but the force output is adjusted accordingly (Figure 5.8).

Figure 5.8 illustrates changes of the discharge rates of Ia and II afferents caused by Myorobotics muscle stretch. For comparison, Figure 5.9b presents the data obtained from simulation of afferents’ behavior. When the muscle is stretched, SEE can immediately change its length, which results into an abrupt positive change in firing rate of Ia afferent. On the opposite, PEE due to its viscosity cannot rapidly change length, hence we see a gradual increases in discharge rate of II afferent. Length of PEE and SEE together constitute muscle length, therefore the latter one decreases after the stretching stops and the former one remains on the same level. Unlike the numerical simulation, the artificial muscle (implemented in hardware) cannot undergo such a sharp change of length, which results consequently into a rather smooth curvature of the sensory fiber response.

Taking into account above presented relationships, it is clear that the Myorobotics actuator in combination with Hill-based controller present a useful approximation of the biological muscle, since they are characterized by equivalent activation and contraction dynamics, as well as the similar sensory feedback.
Figure 5.9: Primary (Ia afferent) and secondary (II afferent) sensory fiber response to stretch.

(a) Myorobotics hardware with Hill-type muscle driver
(b) Simulation of the dynamics of a muscle spindle
Chapter 6
Discussion

A macroscopic Hill-type muscle model (parameterized to reflect the biceps and triceps brachii) was integrated in a soft real-time controller for the Myorobotics series elastic actuator. The controller used the current state of the myomuscle to derive and subsequently apply the force in a biologically plausible manner. Experimental results prove that the Myorobotics actuator exhibits the muscle-like contraction and activation dynamics, subject to actuator’s mechanical constraints.

Mechanical constraints of the robot cause an order of magnitude difference in the maximum contraction velocity of artificial versus biological muscle. Although, the DC motor speed limit does allow its rotation at the speed of the muscle fibers, a number of factors prevent it, such as internal friction or additional load and most importantly software-induced limits. For safety reasons such a limit is necessary, since the muscle units were not initially designed to operate under biologically required velocities. Moreover, for the same reason, a maximum force output of the Myorobotics actuator was limited as well, in order to guarantee control of the robot during the experiments. Nevertheless, our goal was to mimic, not duplicate, biological muscle. The presented system is not yet an analogue of the skeletal muscles, but rather a first approximation of those. It presents a proof of concept that verifies Myorobotics’ ability to replicate the biological muscles dynamical properties.

The objective of this thesis did not include taking into account muscle history. Thus, the notion of muscle fatigue is not present in our system. This limitation can be addressed by implementing an existing dynamic muscle fatigue model, widely present in literature.

The Hill-type muscle driver was controlled by muscle activation decoded from EMG signal of a healthy human subject. As decoders three methods were implemented:

- a polynomial using DWT features
- an ANN with DWT features
• an ANN using signal’s linear envelope (RMS).

Experimental results show a low root mean square error (below 0.13 relative to the measured values) in estimating the muscle activation and high correlation coefficients (exceed 0.75) between predicted and measured values on the testing datasets. When compared to the related studies (force decoding from EMG), our decoders offer a higher variability and adaptability to the incoming signal, since most studies concern themselves with decoding force in a small interval of force (5-10% deviation), while methods presented in this thesis take into account activation levels ranging from 10% to 90% of full muscle activation.

Activation level measurements however are subject to the mechanical limitations of the robot. Values, recorded during experiments, were defined using robot’s coordinate system as reference. Thus, a common calibration object for the human and the robot would improve the accuracy of data sampling and provide an absolute, not relative, reference system.

Another factor limiting accuracy of presented estimators is the data obtained from two EMG channels only. In the elbow flexion/extension task muscle groups involved outnumber biceps and triceps only. Thus, the data recorded from the neighboring muscles, that contribute to the task, could improve the model’s performance. Moreover, these data can be utilized for investigation of muscle synergies and possibilities to mimic them using Myorobotics actuators.

The hardware and network communication limitations have restricted the EMG data sampling rate to 600 Hz. Therefore, running the system on the same machine will possibly improve the sampling rate and subsequently quality of extracted features, especially those using the discrete wavelet transform.

Finally, cross-subject persistence of the model was not achieved in our work, and even remains a valid challenge for the modern scientific community. EMG signal differences stem from multiple factors (electrode placement, skin thickness, size of a muscle), hence a reliable activity (or force) estimator that is able to generalize across subject is still work for future.
Chapter 7

Conclusion

The established connection between an artificial and a biological muscles defines the essential value of the implemented system. First, a series elastic actuator now exhibits dynamical properties similar to a biological muscle. This was achieved through the mapping of myomuscle’s components to the corresponding Hill model elements (series elastic element and contractile element), simulating the ones lacking (parallel elastic element), and implementing a Hill-type driver interface that uses the robot’s current state to derive biologically plausible muscle forces. Second, a one DoF Myorobotics arm (with biceps- and triceps-like actuators) can be controlled in real time by the human biceps and triceps. Activation level of the human muscle is decoded from the EMG signal and then fed into Myorobotics driver interface, which in its turn controls the robot arm and delivers realistic proprioceptive feedback of muscle units.

By leveraging the power of ROS communication standards, system’s components are independent and self-sufficient, hence can be easily replaced, modified, or used individually as:

- a web interface to control and monitor Myorobotics actuators,
- a web interface to monitor online EMG (or EEG) data,
- a macroscopic muscle model (as simulation or connected to Myorobotics),
- an EMG processing module for the muscle force or activation decoding.

Importantly, the developed system does not pose any limitations on the type of contraction (i.e. works with concentric, eccentric, as well as isometric contractions), neither activation levels are restricted. Moreover, we predict muscle activation with EMG, but not force, which might be a more plausible approach since measuring force directly on the muscle is not possible in vivo.
Above listed facts combined, present a suitable test-bed for neuroscientific experiments. By virtue of Myorobotics modularity, various configurations of the body parts can be replicated. Muscle-like controller brings the opportunity to examine muscle synergies in more detail, since it allows to measure force directly on the muscle at the same time driving the muscle using biosignal. Furthermore, in the scenario of task-based operation (prosthetics, teleoperation) proposed system eliminates the necessity to learn the mapping of the robot’s joint, and enables a direct connection between human and robot muscles. Finally, when connected to neuromorphic hardware, spinal cord muscle reflexes could be implemented in a naturalistic way, since the system emulates the sensory fibers as well.
# Appendix A

## Parameters used for the Hill Muscle Model

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<th>Parameter description</th>
<th>Symbol</th>
<th>Value</th>
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<tr>
<td>Optimal length of CE</td>
<td>$l_{\text{CE, opt}}$</td>
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<td>Width of normalized bell curve</td>
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<td>Exponent in the F-L relationship</td>
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<tr>
<td>Hill parameter for contraction dynamics</td>
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<td>Hill parameter for contraction dynamics</td>
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APPENDIX A. PARAMETERS USED FOR THE HILL MUSCLE MODEL
List of Acronyms

ANN  artificial neural network 19, 31, 32, 37, 39–41, 45, 46, 53, 54

BMIs  brain-machine interfaces 5

CE   contractile element 15, 33–35, 42, 43, 47, 49, 53, 54

CNS  central nervous system 5, 11

CWT  continuous wavelet transform 19, 53

DC   direct current 8, 45

DoF  degree of freedom 7, 8, 47, 53

DWT  discrete wavelet transform 27, 29, 30, 37–41, 45, 46, 53, 54

EEG  electroencephalography 47

EMG  electromyography 27, 29, 31

EMG  electromyography 3, 6, 16–19, 21, 23–28, 30, 31, 37, 40, 45–47, 53

GUI  graphical user interface 11, 21, 23, 27

LS   least squares 32

LSL  Lab Streaming Layer 21

MAV  maximum absolute value 29, 30

MUAP motor unit action potential 16, 17, 53

MVIC maximum voluntary isometric contraction 26–28, 53

PCC  Pearson correlation coefficient 37, 38, 54

PEE  parallel elastic element 33, 34, 42, 43, 47, 49, 54
**RMS** root mean square 27, 29, 31, 37, 39–41, 46, 54

**RMSE** root mean square error 18, 37–39, 46, 54

**ROS** Robotic Operating System 21, 23, 24, 35, 47, 53

**SEE** series elastic element 33, 35, 43, 47

**sEMG** surface electromyography 16, 25, 27
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