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Robot Collaboration Partners with Human-like Characteristics in Haptic Object-Manipulation Tasks

Controller Design & Evaluation

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Foreword

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Notations

Abbreviations

ANOVA	Analysis of variance
ARX model	Autoregressive model with exogenous input
BIC	Bayesian Information Criterion
dof	Degree(s) of freedom
fbk	Feedback (experimental condition)
ffw	Feedforward (experimental condition)
GMM	Gaussian Mixture Model
HMM	Hidden Markov Model
if	Individual with full mass (experimental condition)
ih	Individual with half the mass (experimental condition)
p	Partner (experimental condition)
VE	Virtual Environment

Conventions & symbols

Scalars, vectors & matrices

x or X	Scalar
\mathbf{x}	Vector composed of the elements x_i
\mathbf{M}	Matrix composed of the elements M_{ij} (i^{th} row, j^{th} column) and dimension $m \times n$
$\dim(\mathbf{M})$	Dimension of a vector/matrix
$\text{Ker}(\mathbf{M})$	Kernel of \mathbf{M} ; its nullspace
\mathbf{M}^+	Generalized inverse \mathbf{M}
\mathbf{M}^{-1}	Inverse of \mathbf{M} (if \mathbf{M} is invertible)
\mathbf{M}^T	Transpose of \mathbf{M}
\mathbf{I}_ν	$\nu \times \nu$ -dimensional identity matrix
$\mathbf{0}_\nu$	$\nu \times \nu$ -dimensional zero matrix

Mathematical variables & expressions

i	Count variable
J	Objective function

$sgn(x)$	Sign of x
\dot{x} or $\frac{dx}{dt}$	Time derivative of x
\ddot{x} or $\frac{d^2x}{dt^2}$	Second time derivative of x
$\log_b(x)$	Logarithm of x to base b
$\ln(x)$	Natural logarithm of x (logarithm of x to base e)

Statistical variables & expressions

F	F-test statistic
NMSE	Normalized-mean-square error
p	proportion, probability
r^2	Coefficient of determination
R	Residual
$RMSE_x$	Root-mean-square error of x
\bar{x} or μ_x	Mean of x
ρ	Correlation coefficient
σ	Standard deviation
σ^2	Variance
partial η^2	Measure of effect size

Control variables

Signal variables in time domain are denoted in lower case letters and in Laplace domain in the respective capital letters.

D	Damping ratio
e or E	Control error
G	Transfer function (in general)
G_0	Open-loop transfer function
G_p	Plant transfer function
K	Gain
s	Laplace operator
T	Time constant
T_p	Pole (of a standard PID controller)
T_z	Zero (of a standard PID controller)
τ	Time delay

Physical variables

b	Damping coefficient of a viscous damper [Ns/m]
E	Energy [J]
f	Force [N]
f^e	External force [N]
f^i	Internal force [N]
f_o	Resulting force at object's center-of-mass [N]

\mathbf{I}	Rotational inertia matrix [$kg\ m^2$]
k	Spring constant of a linear spring [N/m]
m	Mass/inertia [kg]
t	Time [s]
x	Position [m]
\dot{x}	Velocity [m/s]
\ddot{x}	Acceleration [m/s^2]
τ	Torque/moment [Nm]
τ_o	Resulting torque at object's center-of-mass [N]
ω	Orientation [rad]
$\dot{\omega}$	Rotational velocity/speed [rad/s]

Constants

e	Euler's number
$g = 9.81\ m/s^2$	Gravity
π	Pi

Derived variables

α	Level of assistance, workload/effort-sharing parameter, dominance ratio
\mathbf{W}	Grasp matrix

Subscripts and Superscripts

x_1	Partner 1
x_2	Partner 2
x^d	Desired value of x
x_d	Dyadic
x_e	Experimental/measured data
x_f	Final/end-point value
x_i	Individual
x_m	Model data
x_o	Object (its center-of-mass)
x_s	Slave/follower
x_0	Initial/start value
\hat{x}	Estimate; one out of multiple solutions

Abstract

Many robot application fields, such as robot assistants in industrial or domestic settings, can be further enhanced by a close, physical interaction of humans and robots. It was shown that unilateral, non-interactive approaches like capturing human behavior in an interactive task and replaying the recorded signals are not successful. Instead, collaborative robots are required. To facilitate overlapping workspaces of humans and robots, robotic partners enabling intuitive, haptic human-robot collaboration are, thus, one prerequisite. In their design process, major challenges of haptic interaction are faced: the close coupling of action and reaction as well as active adaptation processes.

This dissertation contributes significantly to this field of research by introducing novel controller solutions for robot collaboration partners and by establishing means for their systematic evaluation. Joint object-manipulation tasks are addressed exemplarily. The applied research approach broadens the focus from providing performance-optimized assistance in task execution to the integration of human-like characteristics into the robot's interaction behavior. It aims at human-like, as one instance of intuitive, interaction behavior in haptic human-robot collaboration.

A model of the object dynamics is presented that is adapted to haptic interaction. In addition to the object dynamics, it enables an in-depth analysis of the variables describing the interaction between the partners. Thus, it allows for a more detailed understanding of the haptic interaction dynamics which forms the basis for a systematic robot controller design. Subsequently, control objectives relevant in haptic human-robot collaboration are derived based on related literature and the two high-level requirements: performance-oriented assistance in task execution and intuitive interaction behavior. Furthermore, a novel, generic control architecture for haptic, robot collaboration partners is established. In combination with the control objectives, this allows for an unprecedented classification and discussion of the state of the art that contributes to this field of research. In the next part, dyadic, haptic, human interaction behavior in a compensatory tracking task is analyzed. And, for the first time, a dynamic control model of the interacting partners is identified experimentally. By this, a deeper understanding of human, haptic interaction behavior is gained: It is shown that the individual's behavior changes when interacting with a partner in contrast to performing the task alone. In accordance with literature, it is suggested that this change in control behavior is related to the internal forces built up between the interacting partners. As the modeling is embedded into a generic experimental paradigm and the control framework, a straightforward implementation on a robotic partner is ensured. Finally, new means to evaluate such robot collaboration partners with respect to human-likeness and task performance are derived based on related work. The presented approach is validated by applying it to the experimental evaluation of two haptic controllers. Results show how evaluation studies contribute to the derivation of guidelines for future robot interaction partners.

Zusammenfassung

Viele Anwendungsbereiche von Robotern, wie Roboter-Assistenten in industriellen oder häuslichen Umgebungen, können durch eine enge, physikalische Interaktion von Menschen und Robotern weiter verbessert werden. Es wurde gezeigt, dass unilaterale, nicht-interaktive Ansätze, wie z.B. das Aufnehmen von menschlichem Verhalten in interaktiven Aufgaben und eine anschließende Wiedergabe, nicht von Erfolg gekrönt sind. Stattdessen sind kollaborative Roboter notwendig. Demnach sind Roboter-Partner, die eine intuitive, haptische Mensch-Roboter Kollaboration ermöglichen, eine Grundvoraussetzung für eine Überlappung des menschlichen und Roboter-Arbeitsbereichs. In deren Designprozess sind die größten Herausforderungen von haptischer Interaktion zu berücksichtigen: die enge Kopplung von Aktion und Reaktion sowie die stattfindenden Adaptionsprozesse.

Die vorliegende Dissertation trägt signifikant zu diesem Forschungsgebiet bei, in Form neuartiger Regelungsansätze für Roboter-Kollaborationspartner und der Etablierung neuer Möglichkeiten für deren systematische Evaluierung. Gemeinschaftliche Objektmanipulationsaufgaben werden exemplarisch behandelt. Der angewendete Forschungsansatz erweitert den Fokus von der Performanz-orientierten Unterstützung bei Aufgabendurchführung auf die Integration von menschenähnlichen Eigenschaften in das Roboter-Interaktionsverhalten. Menschenähnliche, als eine Form von intuitiver, Interaktion in haptischer Mensch-Roboter Kollaboration wird angestrebt.

Ein neuer Lösungsansatz eines physikalischen Modells, ausgerichtet an den Anforderungen haptischer Interaktion, wird präsentiert. Zusätzlich zur Objektdynamik, ermöglicht er eine tiefgehende Analyse der Variablen, die die Interaktion zwischen den Partner beschreibt. Damit ergibt sich ein genaueres Verständnis der haptischen Interaktionsdynamik, welches die Grundlage für einen systematischen Reglerentwurf bildet. Anschließend werden Regelziele für haptische Mensch-Roboter Kollaboration aus der Literatur und basierend auf den abstrakten Anforderungen einer Performanz-orientierten Aufgabenunterstützung und eines intuitiven Interaktionsverhaltens abgeleitet. Außerdem wird eine neuartige, generische Reglerarchitektur für Roboter-Kollaborationspartner etabliert. Diese, in Kombination mit den Regelzielen, erlaubt eine noch nicht dagewesene Klassifikation des Stands der Wissenschaft und leistet damit einen Beitrag zu diesem Forschungsgebiet über den Inhalt dieser Arbeit hinaus. Im nächsten Teil der Arbeit wird das dyadische, haptische, menschliche Interaktionsverhalten in einer Pfadfolgeaufgabe analysiert. Zum ersten Mal wird ein dynamisches Reglermodell experimentell identifiziert. Dadurch ergibt sich ein tieferes Verständnis des menschlichen, haptischen Interaktionsverhaltens: Es wird gezeigt, dass sich das Verhalten des Einzelnen verändert, wenn er mit einem Partner interagiert. Im Einklang mit der Literatur wird nahegelegt, dass diese Änderung des menschlichen Regelungsverhaltens mit den internen Kräften, die zwischen den Partner aufgebaut werden, zusammenhängt. Durch die Einbettung der Modellierung in ein generisches experimentelles Paradigma sowie in die Reglerarchitektur wird eine direkte Implementierbarkeit auf einem Roboter sichergestellt. Zuletzt werden neue Wege für eine Evaluierung dieser Roboter-Kollaborationspartner hinsichtlich Menschenähnlichkeit und Aufgabenperformanz aus der Literatur abgeleitet. Der präsentierte Ansatz wird durch die Anwendung in der experimentellen Evaluation von zwei haptischen Reglern validiert. Die Ergebnisse zeigen wie Evaluationsstudien einen Beitrag zu einem Leitfaden für die Entwicklung von zukünftigen Interaktionspartnern leisten.

1 Towards high-fidelity, haptic human-robot collaboration

By introducing robots, the automation and productivity of industrial assembly lines was and still is improved significantly. However, mainly for safety reasons, there was a strict separation between human and robotic workspace until recently. This prevented robot's even wider spread, in particular leaving industrial settings and moving into human's everyday life. Nowadays, this is changing. The robot's application field is significantly broadened, cf., e.g., Agah [1], Green et al. [61] for extensive surveys. Robots are introduced as, e.g., personal assistants or in robot-assisted surgery. Human and robotic workspaces start to overlap. To gain the most out of these new application fields, recent developments in robotics and human-robot interaction aim at bringing robots and humans into closer interaction. In this context, robotic partners enabling high-fidelity, intuitive, **haptic human-robot interaction** have to be realized. This trend of enabling and enhancing intuitive, haptic interaction between humans and robots leads to increased task performance and usability.

Unilateral, non-interactive approaches like capturing human behavior in a human-human task and replaying the recorded signals [10, 148] are not successful in haptic interaction [148]. Instead, **interactive robots** are required. Early attempts that aimed at such interactive behavior realized leader-follower approaches with the robot as pure follower, cf., e.g., [6, 84, 86, 192]. This means, the *“robot (or team of robots) is (...) viewed as an intelligent tool capable of some autonomy that a human operator commands (...) to perform a task. [However,] This sort of master-slave arrangement does not capture the sense of partnership that we mean when we speak of working jointly with others as in the case of collaboration.”* [74]. Further, these leader-follower approaches are contrary to the findings of Grosz and Kraus [64]: *“Modeling work shows that cooperative behavior arises spontaneously if groups are small and diverse and participants have long-term concerns. If we are going to build systems that will interact on more than one-shot deals, it might be wise to build them with capabilities for collaboration”* [64]. Additionally, the cognitive capabilities of robots increase, and there is a rise of situations where the robot has more, or different, information about task and environment. This information benefit leads only to improved task execution if the robot is more than a pure follower - a partner.

For these reasons, advanced approaches of interactive robots move from pure following to **pro-active** interaction behavior, cf., e.g., [25, 107, 133, 181]. This requires not only knowing, understanding and recognizing the task, the environment and the partner's intention but also control strategies aiming at **successful task execution** as well as **intuitive interaction with the (human) partner**.

Hence, establishing control architectures as well as methods to gain an understanding of human, haptic interaction behavior are key requirements for and challenges in the design of advanced, interactive, haptic robots. This dissertation addresses these challenges by focusing on new concepts that enable robot control of collaborative, haptic interaction behavior in a human-inspired, intuitive way. By this, it contributes to haptic human-robot collaboration, a fascinating and highly interdisciplinary field of research.

The next section presents recent developments in the field of haptic human-robot interaction and is followed up by fundamental definitions forming common ground. Based on this, human-likeness as one instance of intuitive interaction behavior is discussed, and open research challenges are defined in more detail. Finally, the research approach and main contributions of this dissertation are laid out.

1.1 Applications enhanced by haptic human-robot interaction

Haptic human-robot interaction is relevant in a wide range of application areas. It can be categorized not only according to the actual application field, but, also according to the function of the robot within the interaction. The latter aspect significantly determines the appearance and implementation of the robotic system. Thus, it is differentiated between autonomous robots, teleoperation systems and haptic robots mediating haptic human-human interaction in virtual as well as real environments in the following, brief survey.

Fully-/semi-autonomous haptic robots: In the field of autonomous robots, the challenge to solve a joint object-manipulation task in collaboration with a human is faced in many different settings, ranging from industrial to domestic and service applications. The robot is typically introduced to take over the workload in object-carrying tasks as, e.g., presented by Lawitzky et al. [107]. In industrial settings, autonomous robots assist the human, for example, in complex material-handling or micro-machining tasks. This is illustrated by, e.g., Wojtara et al. [216]. There, an autonomous robot supports the precise positioning of a three-dimensional object during the attachment of a windshield to a car body. Similar to fully-autonomous robots, exoskeletons allow an amplification of the human physical strength, cf., e.g., [98].

Leaving industrial environments, high-performance robotic devices are introduced in modern rehabilitation for different physical impairments, like in knee rehabilitation [205] or advanced wheelchair/walking-assist control [96]. Their purpose is to provide optimal assistance to the patient by adapting their control behavior to the patient's current state. Entertainment robots and socially interactive robots are closely related to this. Haptic interaction in social applications occurs, e.g., in handshakes [56, 95, 209, 218] or dancing [78].

Teleoperation Systems: Another type of human-robot interaction is found in teleoperation systems where a human operates a robot in a remote environment and receives

multimodal feedback about the interaction with the remote place. Teleoperation systems extend the human workspace beyond barriers like distance, danger or scaling and allow a human operator to be present in otherwise inaccessible environments like space, subsea or disaster areas. For more details please refer to, e.g., Hokayem and Spong [76], Sheridan [169]. Furthermore, experts can act in remote locations without the necessity of traveling. Another large application area of teleoperation systems are robot-assisted surgical systems where haptic feedback was introduced only recently [135]. Finally, teleoperation setups allow a skill transfer from humans to autonomous robots by applying learning-by-demonstration strategies, see, e.g., [20]. It is important to provide haptic feedback in teleoperation applications in order to achieve high system performance and transparency.

Technically-mediated, human interaction in real and virtual environments: The haptic modality is also added to systems that enable technically-mediated human-human interaction. This means that two (or more) humans interact with each other via a technical system. Application examples are found mainly in the area of multi-user virtual environments [23, 48] or multi-user teleoperation setups [18]. Adding haptic feedback provides a more realistic feedback to the users. In case of virtual environments (VE), it is additionally aimed at increasing immersion. Immersion refers to the degree to which the user feels to actually be in a virtual environment. It can be increased by providing not only visual feedback to the user but also by playing back the haptic interaction of the user's avatar with the virtual scene. For example, in motor-skill learning for surgery [39, 131], the teacher, i.e., experienced surgeon, guides the student how to make a special motion or cut. Typically, the student receives feedback from the virtual tissue as well as from the teacher. Thereby, special algorithms are required to fuse the signals of the involved parties.

Despite the research activities in all of these application fields, there are several remaining challenges. Before defining the research challenges in more detail, fundamental definitions are introduced, and human-likeness is introduced as one instance of intuitive interaction.

1.2 Fundamental definitions

In human-robot interaction, *interaction* commonly refers to a bidirectional, causal signal exchange between two or more *systems*, here, typically represented by interacting *partners*. Within the context of this thesis, most discussions assume two partners, but the extension of the presented ideas to multiple partners is straightforward. As already demonstrated in the previous paragraph, the interacting partners may be either *human* or *artificial*. Further, an artificial partner can have a *robotic* or *virtual* realization. Depending on the involved partners, it is distinguished between *human-human interaction* and *human-robot interaction*¹. Depending on the number of robots and humans interacting with each other,

¹The more general term of *human-agent interaction* could be applied as well because many of the presented approaches apply to virtual and robotic partners the same way. However, as the focus of this dissertation is on the design of robotic partners, human-robot interaction is used in the following.

it can be thought of a large variety of interacting groups consisting of different human-robot ratios [219].

While the analysis of human-robot interaction via speech and gestures is rather advanced, the topic of haptic human-robot interaction is still underrepresented. In general, *haptics* comprises tactility, kinesthesia, pain and the perception of temperature [108]. In the field of human-machine interaction, tactility and kinesthesia are mostly considered. According to Srinivasan et al. [177], *tactility* is the perception of “*contact with the object, mediated by the responses of low threshold mechanoreceptors innervating the skin (...) within and around the contact region*” [177]. In contrast, *kinesthesia* is defined to be “*the sense of position and motion of limbs along with the associated forces*” [177]. Grounded in this definition, throughout this thesis *haptic interaction* refers to the kinesthetic, bidirectional exchange of force and position signals between interacting partners.

In general, a human or a robot can *interact haptically* with a (passive) environment, or there may be haptic interaction between two partners. This two-way communication [66] is one characteristic of haptics contrasting it to other modalities. It involves the human, haptic perceptual and motor system at the same time. From a technical point of view, sensors and actuators are fused in one device, i.e., the human/robot arm. This simultaneity of action and reaction is one of the main challenges in haptic interaction research. Another characteristic of haptic interaction is the close physical coupling of the systems involved. If humans interact with their environment haptically, they are in physical contact with the environment, and, hence, they act on the environment and modify it, even if they just aim at exploring their surroundings. This is one of the main differences to other modalities like vision or audio, with which the environment can be perceived without acting on it. Exploring the environment haptically, hence, requires the human to act as a controller in all situations.

In case of haptic interaction between two partners, *sequential* interaction like handing-over an object [36, 112, 156] and *simultaneous* interaction are differentiated [9]. In case of simultaneous interaction, either direct or indirect physical contact of the partners is considered. Examples are handshaking [207], dancing [77] or rotational and translational joint object manipulation [148, 224]. In Burghart et al. [17], a more detailed classification is presented. The focus of this dissertation is on **simultaneous haptic manipulation of physical or virtual objects by two partners, either human or robot**. The object establishes a link between the two partners, hence, an interacting *dyad* is formed. Analyzing the behavior of two interacting partners, physical and derived variables can be evaluated either on

- a *dyadic* level by, e.g., the motion of the object or task performance or
- an *individual* level by, e.g., applied forces or energies.

It is characteristic to haptic interaction that some variables can be addressed on a dyadic-level-only because of the above-introduced non-causality of action and reaction.

In literature, different types of interaction like *collaboration* or *competition* are distinguished in dependence of the involved partners' intentions and actions. *Intentions* are “states of minds that are usually seen to precede thoughtful action, in striving towards sought-after outcomes” [109]. Depending on the reference [15, 21, 61, 64, 139, 167], the classifications and definitions of interaction types vary. In the context of this thesis, *collaboration*, *cooperation* and *joint action* are used interchangeably and refer to “a special type of coordinated activity, one in which the participants work jointly with each other (...) to satisfy a shared goal” [64]. In contrast to interaction that “entails only acting on someone or something else, collaboration is inherently 'with' others; working (labore) jointly with (co).” [63] (similar in Green et al. [61]). Hence, based on a *shared goal*, i.e., the same overall intention that both partners have, a *dyadic action plan* as well as *individual action plans* for each partner have to be negotiated [189] and, then, executed.

According to Sebanz et al. [166], this *intention negotiation* involves

a) predicting the actions of the partner, commonly referred to as *intention recognition* or *intention estimation*, and

b) *integrating* the predicted effects into one's own planned actions.

Therein, these effects are predicted continuously based on a-priori knowledge and feedback received from the environment. The *intention integration* involves decision-making as well as adaptation processes. *Decision-making* generally refers to the act of choosing one available option out of several possibilities. Referring to Hardy-Vallée [68], the “standard philosophical conception of decision-making equates deciding and forming an intention before an action” [68]. *Adaptation* describes the adjustment to changing environmental conditions, here, referring mainly to the perceived environmental feedback, in particular the partner's behavior. Hence, adaptation can be understood as a continuously on-going process of decision-making based on new information.

To allow the partner to infer one's own intentions and, based on this, enable a successful intention integration, related information has to be exchanged. *Communication*, a “special interaction mechanism” [47], provides the means. It refers to the transmission of signals containing information, i.e. the *message*, from a *sender* via a *communication channel* to an intended *receiver*.

Once the action plans are negotiated, the desired individual behavior is determined and has to be executed. This collaborative task execution requires the design of appropriate interactive control approaches which require special attention if haptic robot behavior is designed.

As an example, the concept of intention negotiation and collaborative control is applied to a haptic task where the shared goal is to carry an object from place A to B. The two partners have to agree on a dyadic action plan which commonly consists of a desired object trajectory (or trajectory of the interaction point of their hands) or force profile. Based on this, the partners determine their individual contribution to task execution by their individual action plans. These individual action plans are the *roles* of an *interaction strategy* that each partner takes on. For a human-robot team, this is, for example, if the robot takes over the whole workload, and the human gives directional cues only. Please

note that roles can change over time, i.e., each partner's contribution to the task varies, though the *interaction strategy*, i.e., the way how the role is determined, remains constant.

Finally, one prerequisite for a collaborative robot is *cognition* featuring robotic perception-action loops. Therefore, advanced sensors, like cameras, position encoders or force sensors, for *perception* and actuators, like motors, enabling *actions* are required. The *processing* of the sensor data and reasoning about intended actions is typically realized by information-processing and control algorithms. As the focus of this dissertation is on gaining new insights into collaborative, haptic interaction behavior rather than in the complex perception-action loops recently provided in high-level cognitive robots, the interested reader may refer to Vernon et al. [200] for a more detailed survey.

Next, the aspect of intuitive interaction behavior is addressed in more detail.

1.3 Human-like, as one instance of intuitive, interaction behavior

So far, interactive robots commonly assist the human partner in efficient, high-performance task execution. This is achieved by focusing on gaining and modeling task knowledge, compare, e.g., [25, 122]. Then, this task knowledge is integrated into appropriate controllers together with simple, mainly technically-driven interaction strategies, cf., e.g., [25, 122, 133]. This approach is valid in the development of assistive robots applied in highly-structured tasks and scenarios. However, to pave the way for continuous, physical human-robot collaboration in everyday life, more facets have to be dealt with: The human has to accept and rely on the robot. To achieve this acceptance, the interaction with the robotic partner has to be intuitive and familiar to the human. Hence, intuitive interaction is – like for all technical devices designed for human-machine interaction – a key requirement. However, only few approaches that focus on haptic interaction behavior with a human partner aim especially at intuitive collaboration [133, 148, 209]. Among other reasons, this is due to the main challenge in this context: the definition and identification of “intuitive interaction”.

Because humans interact with each other regularly in everyday life, they are used to and have adapted to human-like interaction patterns. In other words, their present experiences and, thus, the mental models that form their knowledge base, were acquired in human interaction scenarios. Hence, one approach to achieve intuitive, haptic human-robot collaboration is the design of intelligent, human-like interaction partners [61, 129, 153]. In more detail, Nass et al. [129] have “*shown that the human-computer relationship is fundamentally social. The results suggest that many other principles drawn from the extant literature in social psychology, communication, and sociology are relevant to the study of human-computer interaction and have clear implications for user interface design*” [129]. Further, in Hinds et al. [71] it is argued that humans “*will be more at ease collaborating with human-like*” [71] than with machine-like robots because they “*may be perceived as*

more predictable” [71], and “human-like characteristics are likely to engender a more human mental model of the robot” [71], when estimating its capabilities. This seems to be of particular importance in haptic interaction due to the close physical contact and the overlapping work spaces.

Still, aiming at human-like interaction behavior does not infer the exact replication of human behavior in every detail for two reasons:

1. Considering familiarity of appearance and motion of an interactive robot and plotting it as a function of human-likeness, the “*uncanny valley*” can be observed, referring to Mori [128]: The more human-like the robot, the more familiar it appears to a human, and hence, the graph of this function rises up to a certain point. Then, if the robot is almost “human”, there is a sudden drop in the function, the “*uncanny valley*” where “*the subtle imperfections of the recreation become highly disturbing*” [47], and the human is irritated by the robot. It is unclear until now if an equivalent to this uncanny valley of robot appearance exists in haptic interaction.
2. The main potential of technical partners, in contrast to humans, lies in their high accuracy and repeatability of tasks as well as their high physical workload. Realizing human-like robots implies directly giving up some of their potential.

Nevertheless, because of the need for intuitive collaboration enabling continuous interaction, providing human-like behavior is a key feature of collaborative robots. Following this line of reasoning, control models describing the main human interaction characteristics, if implemented on robots, are a prerequisite to enable intuitive, haptic human-robot collaboration.

1.4 Open challenges

Applying the above-presented definitions, the open research challenges are now identified and discussed in detail.

Haptic interaction, as required in the previously introduced application fields, represents a major challenge in this control context: the close coupling of action and reaction as well as adaptation processes have to be considered in a systematic control design and evaluation of robot partners in order to enable haptic human-robot collaboration. In such *human-in-the-loop* systems, the human and the technical system act as controllers that perform different actions. By these actions, they influence each other’s state as well as the state of the overall, closed-loop system. Thus, a human-centered design and development of the robotic systems is required to achieve efficient and intuitive interaction.

A typical task of haptic collaboration is joint object manipulation, i.e., a human acts together with a technical haptic partner (e.g., semi-/autonomous robot, teleoperator) on a

common object. Control strategies established for this representative task can be applied to a wide field of applications.

In literature, various approaches and control strategies enabling haptic, interactive behavior of robots in joint object-manipulation tasks can be found in, e.g., Calinon et al. [20], Lawitzky et al. [107], Wojtara et al. [216]. Still, the following open research challenges are identified:

1. **A model of the plant dynamics adapted to haptic interaction:** A first important component in every controller design is a model of the *plant* to be controlled. This is necessary as it enables a systematic analysis of the system under consideration and its control variables. And, it leads to a deeper understanding of the challenges to be considered in the actual controller design. Common models found in literature are dynamic models of the closed kinematic chain formed by the two partners, the object and, possibly, of the broader environment. These dynamic models are typically over-determined with redundant degrees of freedom (dof) and, thus, have multiple solutions. Solutions known from haptic robot-robot interaction focusing on task execution are adopted. But, an adaptation fitted to the challenges faced in human-robot collaboration, in particular, the interaction between the partners, has not been presented in literature to the author's best knowledge. However, such a model is required for an integral analysis of task and interaction dynamics. It forms the basis for the development of controllers that realize not only efficient task execution but, at the same time, intuitive interaction behavior with the partner. This directly leads to the next open research challenge.
2. **Control objectives in haptic human-robot collaboration:** Performance and intuitive interaction are key requirements for successful haptic human-robot collaboration. However, there is a gap between these high-level requirements and the definition of explicit control goals that can be implemented in controllers. Therefore, the definition and systematic derivation of control objectives in the context of haptic human-robot interaction has to be addressed.
3. **A generic control architecture of a robotic, haptic collaboration partner:** To change over to the actual control structures next, most approaches presented in literature focus on specific research challenges that solve certain sub-problems of this complex challenge. Though this is a valid and proven method, a combination and/or fusion of the different solutions by a generic control framework that enables synergetic effects is still an open challenge.
4. **Dynamic model of human, haptic interaction behavior in collaborative tasks:** Referring to section 1.3, integrating human characteristics into interactive control strategies is a key feature to achieve intuitive, haptic interaction behavior of collaborative robots. This requires an understanding and modeling of haptic, human interaction behavior. However, only very few human, haptic interaction control models (e.g., [148]) have been identified up to date.

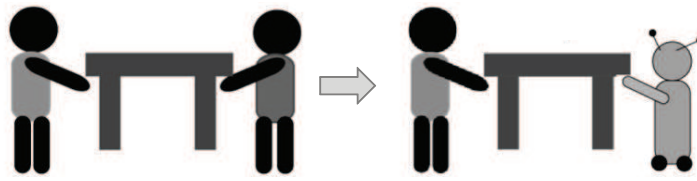


Fig. 1.1: Research approach to achieve robotic, haptic collaboration partners providing assistance in task execution as well as intuitive interaction behavior: Transferring knowledge gained in human-human collaboration to human-robot collaboration

5. **Evaluation of collaborative controllers:** Once intuitive haptic, human-like control strategies are identified, it is necessary to evaluate them. If optimization of task performance is addressed, objective measures for such evaluation studies are commonly easily defined. However, the definition and objectification of *human-likeness* in the context of haptic human-robot collaboration is still an open research question. Furthermore, as the control strategies aim at high performance and, at the same time, intuitive interaction, evaluation methods have to be established that describe the relation of these goals. This is to enable, if necessary, a systematic trade-off between them.

To address these research challenges, the approach introduced and discussed in the next section is applied in this thesis.

1.5 Approach

In this dissertation, an integral approach for a controller design of technical partners with human-like characteristics in dyadic, haptic human-robot collaboration and their systematic evaluation is applied to address the challenges introduced in the previous section. It is aimed at establishing a generic procedure to derive controllers for haptic human-robot collaboration. The key requirements of these controllers are a) to provide assistance to the human for improved task performance and b) to enable the robot to send and receive the most relevant signals characteristic to haptic, human collaboration in order to achieve intuitive interaction. The developed procedure is applied to dyadic, collaborative object-manipulation tasks.

There are generally two means to achieve this goal:

1. First, human behavior is analyzed in haptic human-human interaction and respective control models are derived. In a second step, these findings are transferred to haptic human-robot interaction as depicted in Fig. 1.1.
2. Human behavior is analyzed directly in human-robot interaction, cf., e.g., [107, 122], and the robot's control behavior is gradually adapted to the user's needs by evaluating different iterations.

In this dissertation, the first approach is chosen for the following reasons: First, realizing initial robot controllers enabling interactive behavior is a challenge. Even more important is that human partners potentially modify their behavior if in interaction with a robot. This is because they estimate or know the robots capabilities and, intentionally or unintentionally, adapt their actions to it. Hence, no real intuitive, in the sense of human-like, interaction is achieved. Additionally, the first approach is well established and has been successfully applied in related fields of research. This is demonstrated by the following example of realizing human, dynamic arm characteristics on a robot: Early work in biomechanics [30, 46] revealed that the human arm shows spring-like behavior. Based on this first model structure, the dynamic parameters of the human arm impedance were identified by various studies, compare, e.g., [59, 70, 144]. It was analyzed how humans adjust their arm-impedance parameters in dependence of the environment they interact with. Based on these results, “biologically-inspired” robots [50, 201, 202] were realized, then.

A closer look at the first approach shows that it is not sufficient to conduct human interaction studies only. A more integral approach has to be established to enable a successful transfer to robotic systems: In order to derive control guidelines as well as control algorithms, a dynamic model of the plant, i.e., the kinematic chain formed by the interacting partners, explaining the underlying variables of haptic interaction has to be introduced. Furthermore, due to its complexity, human interaction behavior is usually analyzed and modeled with respect to specific research questions. To enable an integration of these findings, a generic control architecture of haptic collaboration has to be established. Within such a control framework, the different components required for the realization on a robotic system have to be defined. Once the findings of human, haptic interaction behavior were transferred successfully to and implemented on a robot, it has to be evaluated systematically in a user study. By this, performance and acceptance by the user are assessed. If designed thoroughly, the results provide directions for future developments. Hence, an iterative design and evaluation process is adopted which is similar to approaches established for the user-centered design of interactive systems (ISO 9241-210:2010, [88]) emphasizing the interdisciplinary focus of the work.

1.6 Outline & main contributions

The previously-presented integral approach for control design of a technical partner with human-like characteristics in dyadic, haptic human-robot collaboration and its systematic evaluation is broken down into the following chapters. Additionally, their main contributions are highlighted.

In the following chapter, a **physical, dynamic model** of the closed kinematic chain formed by the two haptically interacting partners and their joint object is introduced. The relevant dynamic equations are set up. A solution particularly adapted to the characteristics of a controller design for haptic human-robot collaboration is derived. Based on this, a discussion of the involved control variables and the subsequent challenges is enabled for

the first time. Furthermore, the main differences between haptic robot-robot and haptic human-robot interaction with respect to robot control design are stressed. These findings form the basis for all other chapters.

In chapter 3, **control objectives** in the context of haptic human-robot collaboration are identified. And, a new **generic control framework** that applies to haptic human-robot collaboration is set up and discussed. The latter consists of different modules that distinguish different levels of interaction. This enables not only a modular controller design with distinct interfaces but also – in combination with the respective control objectives – an unprecedented classification of the current state of the art. By this, synergetic effects are to be exploited, e.g., by a combination of different approaches. Furthermore, this classification is the basis for the identification of future research challenges as well as a systematic design of advanced haptic collaboration partners.

For the framework’s “interaction controller module”, one research challenge is the **identification of task-specific control models** that reproduce human interaction characteristics. This is approached in chapter 4: A task-specific, human performance model for compensatory tracking tasks is successfully transferred to haptic, human collaboration behavior. In more detail, McRuer’s crossover model [119] is a well-established method to describe the behavior of *one* human operator performing such a haptic task. Here, McRuer’s approach is extended to two human operators performing the task, collaboratively. Furthermore, the following questions are addressed: a) Do interacting partners adapt their behavior to each other and to the task in such a way that the crossover model can still be applied to the interacting dyad?, and b) Does the individual’s behavior change when interacting with a partner in contrast to performing the task alone? To answer these questions, transfer functions of control models describing the dyadic as well as individual behavior are derived. The respective model parameters are identified based on experimental data, and the good model fit is validated. Hence, a human performance control model of an individual person performing a compensatory tracking task in collaboration with a human partner is successfully identified for the first time allowing a straightforward implementation on a robotic partner.

Finally, in chapter 5, a systematic approach to **evaluate haptic, technical partners with human-like characteristics** is presented. As an integration of human-like characteristics into interactive controllers is a new direction of research, methods to evaluate this human-likeness is also in its early stages. Thus, in the first part of this chapter, approaches to evaluate human-likeness in haptic human-robot collaboration are introduced and classified based on a review of related work. Based on this, measures are introduced that allow to determine the degree of human-likeness of haptic interaction partners on a continuous scale. This is important to enable a systematic comparison of different implementations with each other. In doing so, two subjective rating methods are proposed. Furthermore, task performance is evaluated, and a correlation of the subjective human-likeness measures with the task-performance measure is conducted. This is added to the evaluation to take account for the two key requirements of haptic collaboration: high performance and intuitive interaction. To demonstrate the applicability and validity of the proposed

procedure, it is applied in an experiment to compare two different implementations of a haptic interaction partner: a feedforward model based on a force-replay and a feedback model. The interpretation of the results leads to the formulation of guidelines for future robot implementations.

Summarizing these main contributions, this dissertation broadens significantly the state of the art in the field of controller design and evaluation of technical partners with human-like characteristics in haptic joint object manipulation. This is elaborated in detail in the last chapter.

2 Physical model of object dynamics in interactive, haptic manipulation tasks

The first step in controller design is always the **analysis of the plant to be controlled**. Most importantly, its general structure, variables and dynamics are to be determined. By this, valuable insights into its characteristics are gained, and conclusions about control requirements can be drawn. Based on this, adequate control objectives and controller structures can be derived. Considering dyadic collaboration in manipulation tasks, the plant to be controlled is the joint object. Both of the partners apply forces to the object at their respective interaction points. By this, they control its behavior collaboratively. This is illustrated by the block diagram in Fig. 2.1.

Due to redundant degrees of freedom, the dynamic model is not unique. Different solutions may be defined. In the following, a **dynamic model is introduced that is particularly adapted to dyadic, joint, haptic manipulation**. The chosen approach is embedded into and discussed based on related literature. It is a modification and fusion of existing approaches. The focus is broadened from object motion to the interaction between the partners. It aims at a physically feasible and intuitive description of an interacting dyad, focusing on, but not restricted to, human-robot pairs. This dynamic model serves as basis for a **discussion of feasible states in dyadic interaction as well as the control to a desired state**. Hereby, robot-robot collaboration is contrasted to human-robot collaboration.

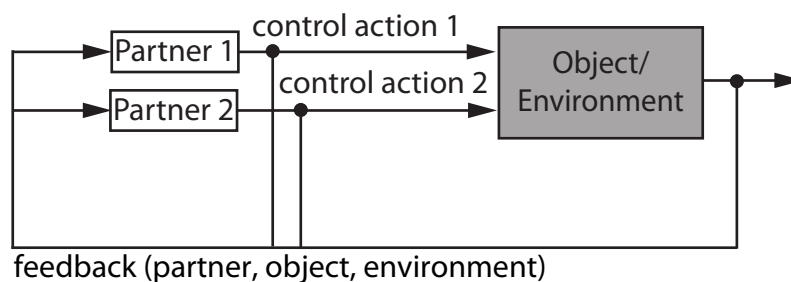


Fig. 2.1: Block diagram of two collaborating partners in closed-loop dyadic object manipulation. The focus of this chapter is on the object (=plant) dynamics.

2.1 Related work

In different research areas, dynamic models of interacting dyads are presented taking into account the close physical coupling of the partners. To describe the synchronization dynamics of a physically coupled dyad, oscillators are widely suggested, compare, e.g., [95, 159]. However, the method of oscillators is mostly applied to tasks with cyclical task trajectories, and it is not well-suited for object-manipulation tasks.

In **social sciences**, a completely different research area, dynamic interaction models in form of differential equations are formulated to describe the influence of one partner's behavior on the other one's [16, 43] in, e.g., long-term relationships. The model of Felmlee and Greenberg [43] is presented as an instance:

$$\dot{x} = \frac{dx}{dt} = a_1(x^d - x) + a_2(y - x) \quad (2.1)$$

$$\dot{y} = \frac{dy}{dt} = b_1(y^d - y) + b_2(x - y) \quad (2.2)$$

where x and y are a certain behavior of partner 1 and 2, respectively. x^d and y^d is each partner's desired behavior. Though not related to haptic collaboration, equations (2.1) and (2.2) resemble a dynamic system in state-space representation describing the coupling of two human, dynamic systems. If this approach was applied to haptic collaboration, the main challenges would lie in the definition of appropriate states as well as in- and output variables. Furthermore, the desired behavior, i.e., the control objectives as well as suited control laws had to be identified.

In **robotics**, object manipulation with multiple manipulators, e.g., robot arms or fingers, is an intensively explored field. In the following, only the work most relevant for this dissertation is presented. The interested reader is referred to, e.g., Bicchi [12] for a more detailed literature survey. In general, the main interest of these approaches is the design of controllers enabling dynamic object manipulation with multiple robotic arms or fingers and, at the same time, ensure a stable grasp of the object without damaging it. Achieving both of those control objectives is enabled by the control of manipulation and grasp forces, e.g., [80, 126, 162, 184, 211]. Like in haptic human-robot collaboration, the dynamics of the closed kinematic chain built by the two robot manipulators and the object have to be modeled for the controller design.

In this context, workload sharing, i.e., each partner's contribution to the manipulation forces and the internal forces that are built up within the object but do not contribute to its motion, are key issues. Many different definitions of them have been introduced in the fields of multi-robot, human-human and human-robot interaction.

Commonly, equal workload sharing approaches are chosen in robotics for coordination controllers leading to efficient solutions [81, 104, 162, 223]. For example, in Hsu [81], a coordinated control of multiple manipulator systems is presented where internal and external forces are controlled separately. In Uchiyama et al. [196], an asymmetric workload

sharing is realized by a hybrid position/force control for two robots arms holding a common object. The asymmetric workload sharing was chosen because equal load sharing led to decreased performance if external disturbance forces were applied on the object. Their key point is the introduction of a workload sharing matrix¹ \mathbf{A} defining how workload is shared among N arms. As another instance, Zheng and Luh [223] explain demonstratively the definition of a load distribution, its optimal choice and role in robot manipulation tasks.

In Rahman et al. [145], a **human-human** object-carrying task in 1 dof is considered where the motion of the object is described by Newton's law

$$m_o \ddot{x} = f_1 + f_2 \quad (2.3)$$

with m_o the mass of the object, and f_i ($i \in \{1, 2\}$) is the force applied by the partners. Further,

$$f_1 = \alpha_1 m_o \ddot{x} + f^i, \text{ and} \quad (2.4)$$

$$f_2 = (1 - \alpha_1) m_o \ddot{x} - f^i \quad (2.5)$$

where they call α_1 a “*distribution ratio of the inertia load*” [145], and f^i is the internal force. Because, according to them, “*the nature of the internal forces is unknown*” [145], they deduce α by correlating the force applied by the participants with the resulting acceleration of the object. They argue that the higher the correlation coefficient is the higher the contribution of the respective participant is to the motion of the object. However, one drawback of this model is that it is not complementary, i.e., if partner 1 and 2 interact, $\rho_1 + \rho_2 = 1$ does not necessarily hold. However, α is complementary ($\alpha_1 + \alpha_2 = 1$) and describes that the more one partner leads the more the other follows. A similar construct is introduced by Reed et al. [149] referring to the *dominance* ratio of the interacting partners for a 1-dof rotational task. There,

$$\alpha_1 = f_1 / (f_1 + f_2), \text{ and} \quad (2.6)$$

$$\alpha_2 = f_2 / (f_1 + f_2). \quad (2.7)$$

This definition is complementary for their special case that the sign of the forces f_1 and f_2 is the same.

To describe the workload sharing, the ratio $W = F_{robot} / F_{human}$ relating the force applied by the robot to the force applied by the human in a human-robot object-carrying task is introduced by Al-Jarrah and Zheng [4]. In Wojtara et al. [216], a weight separation is suggested in the positioning of a flat object for advanced **human-robot interaction**. In Lawitzky et al. [107], the workload is determined to control task performance as well as effort sharing to a desired value in a 2-dof object-carrying task of a bulky object executed by a human and a robot.

¹In the original work, named \mathbf{K} .

In summary, the definitions of a dominance or workload-sharing parameter α in haptic human-robot collaboration are equivalent to the definition of workload sharing or load distribution established in robotics.

Based on this literature, a physical model of interacting partners is introduced in the following. This enables the analysis and discussion of the plant variables, i.e., the forces and motion of the manipulated object and the derivation of conclusions about robot control behavior in collaborative, haptic human-robot tasks.

2.2 Model

In the following, a model of interaction dynamics is introduced and discussed by fusing mainly the robotic approaches presented in literature. For this model derivation, the nature of the partner, human or robot, is not relevant, and it is generally referred to as a partner. The differences between robot-robot interaction and human-robot interaction are approached in 2.3, the discussion of this chapter.

For the derivation of a physical, dynamic model of an interacting dyad, force and motion variables are most relevant. They are discussed in the following describing the coupling of the partners via a common object in dyadic object manipulation. As dyadic interaction is the focus of this dissertation, two interacting partners ($N = 2$) are considered in the following. As depicted in Fig. 2.2, both partners *apply wrenches*, i.e., forces \mathbf{f}_i ($i \in \{1, 2\}$, $\dim(\mathbf{f}_i) = 3 \times 1$) and moments $\boldsymbol{\tau}_i$ ($i \in \{1, 2\}$, $\dim(\boldsymbol{\tau}_i) = 3 \times 1$), at their interaction point with the object

$$\mathbf{f} = \begin{bmatrix} \mathbf{f}_1 \\ \boldsymbol{\tau}_1 \\ \mathbf{f}_2 \\ \boldsymbol{\tau}_2 \end{bmatrix}. \quad (2.8)$$

Generally, the partners can apply wrenches in all six degrees of freedom. However, the manipulable degrees of freedom depend on how the object is grasped. A good overview of different grasp strategies and their implications on wrenches that can be generated in the context of robot grasping is presented by Uchiyama et al. [196]. A general rigid grasp is assumed enabling the partners to apply wrenches in all 6 dof.

If a *resulting force* \mathbf{f}_o and *moment* $\boldsymbol{\tau}_o$ act on the center of mass of a rigid object with inertia $\mathbf{M}_o = m_o \mathbf{I}_3$ where \mathbf{I}_3 is a 3×3 -dimensional identity matrix and moment of inertia \mathbf{I}_o , its dynamic behavior is generally described by Newton and Euler equations:

$$\mathbf{f}_o = \mathbf{M}_o \ddot{\mathbf{x}}_o \quad (2.9)$$

$$\boldsymbol{\tau}_o = \mathbf{I}_o \dot{\boldsymbol{\omega}} + \boldsymbol{\omega} \times (\mathbf{I}_o \boldsymbol{\omega}) \quad (2.10)$$

where \mathbf{x}_o and $\boldsymbol{\omega}$ are the position and orientation of the object's center of mass expressed in a global reference frame. Its first and second derivative are the object's translational and rotational velocity and acceleration, respectively.

The resulting wrenches² are caused by the wrenches applied by the partners on the object as well as inertial forces. Here, as the center of mass is of interest, their gravitational and centrifugal components have to be considered:

$$\mathbf{f}_o = \sum_{i=1}^{N=2} \mathbf{f}_i + m_o \mathbf{g} \quad (2.11)$$

$$\boldsymbol{\tau}_o = \sum_{i=1}^{N=2} \boldsymbol{\tau}_i + \sum_{i=1}^{N=2} \mathbf{r}_i \times \mathbf{f}_i \quad (2.12)$$

where $\mathbf{g} = [0 \ 0 \ -g]^T$ is the gravity vector and $\mathbf{r}_i = [r_{i1} \ r_{i2} \ r_{i3}]$ is the position of the i th partner's interaction point with the object with respect to the object's center of mass.

Substituting equations (2.11) and (2.12) in equations (2.9) and (2.10), leads to

$$\mathbf{M}\ddot{\boldsymbol{\phi}} + \mathbf{Q} = \mathbf{W}\mathbf{f} \quad (2.13)$$

where

$$\begin{aligned} \mathbf{M} &= \begin{bmatrix} m_o \mathbf{I}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{I}_0 \end{bmatrix}; & \ddot{\boldsymbol{\phi}} &= \begin{bmatrix} \ddot{\mathbf{x}}_o \\ \dot{\boldsymbol{\omega}} \end{bmatrix}; & \mathbf{Q} &= \begin{bmatrix} -m_o \mathbf{g} \\ \boldsymbol{\omega} \times (\mathbf{I}_o \boldsymbol{\omega}) \end{bmatrix}; \\ \mathbf{W} &= \begin{bmatrix} \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 \\ \mathbf{R}_1 & \mathbf{I}_3 & \mathbf{R}_2 & \mathbf{I}_3 \end{bmatrix}; & \mathbf{R}_i &= \begin{bmatrix} 0 & -r_{i3} & r_{i2} \\ r_{i3} & 0 & -r_{i1} \\ -r_{i2} & r_{i1} & 0 \end{bmatrix}. \end{aligned}$$

Simplified, the left side of equation (2.13) resembles the general load of the object (dynamics) and the right side the effect of the forces applied by the interacting partners on this load. \mathbf{W} is commonly called *grasp matrix*. It describes a) the relation between the general load and the force applied by the interacting partners, and b) how the load is shared between the interacting partners. More details on the latter aspect follow in the next paragraphs.

In object manipulation, the control of the object's motion is a key issue independent of the number of partners executing the task. Hence, it is of interest, what forces have to be applied to the object (by the partners) to cause a certain resulting force on the object and, thus, a desired motion. Hence, equation (2.13) has to be solved for \mathbf{f} . The general

²In the following, the wrenches are described from an "object-point-of-view", meaning that they are decomposed based on how they act on the object. The interested reader is further referred to Pan et al. [138] where forces applied by a human are discussed from a "human-arm-point-of-view".

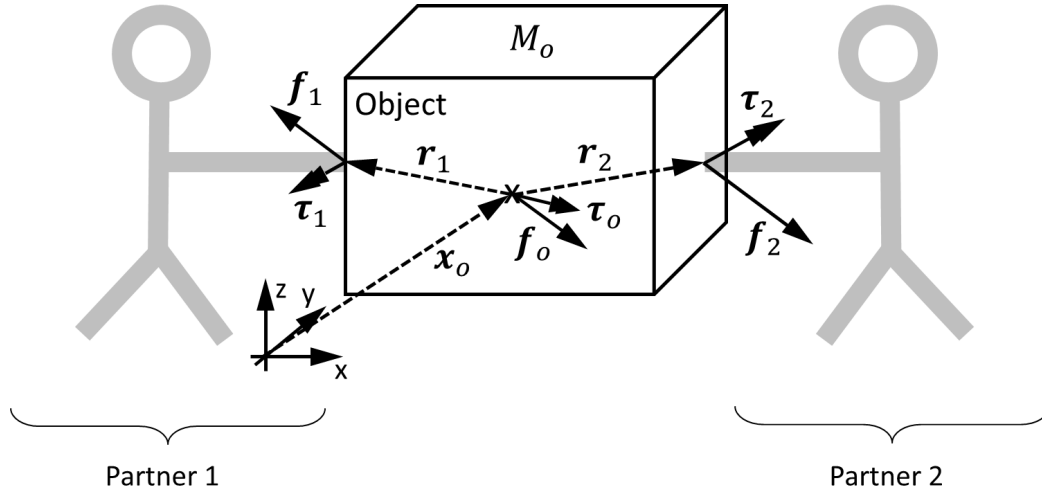


Fig. 2.2: Two partners grasping a common object with inertia M_o (and moment of inertia I_o) rigidly and manipulating it: x_o is the position (and orientation) of the object's center of mass expressed in a global reference frame. The resulting force f_o and moment τ_o act on the center of mass. f_1 and f_2 are the forces applied by the interacting partners at their interaction points with the object (r_1 and r_2 describe their position with respect to the object's center of mass.). τ_1 and τ_2 are the respective moments.

solution is given by

$$\mathbf{f} = \underbrace{\mathbf{W}^+(\mathbf{M}\ddot{\phi} + \mathbf{Q})}_{\mathbf{f}^e} + \mathbf{f}^i \quad (2.14)$$

where \mathbf{W}^+ is a generalized inverse of the grasp matrix \mathbf{W} . \mathbf{f}^i lies in the nullspace of \mathbf{W} and is given by its kernel $\text{Ker}(\mathbf{W}) = \{\mathbf{f} | \mathbf{W}\mathbf{f} = \mathbf{0}_6\}$. It is called *internal or squeeze force/wrench* and does not cause any object motion. \mathbf{f}^e is called *external or manipulation force/wrench* as it describes each partner's contribution to the object's motion.

Because, here, $\dim(\mathbf{W}) = 6 \times 12$, the matrix is redundant, and its inverse \mathbf{W}^+ is not unique. Many different solutions for \mathbf{W}^+ and \mathbf{f}^i that solve equation (2.14) are presented in literature, see, e.g., Doty et al. [31], Hollerbach and Suh [79] for an in-depth discussion. In the following, $\hat{\mathbf{W}}^+$ is written if a particular solution of \mathbf{W}^+ is presented and discussed.

The weighted **generalized Moore-Penrose pseudoinverse**

$$\hat{\mathbf{W}}^+ = \mathbf{P}^{-1}\mathbf{W}^T(\mathbf{W}\mathbf{P}^{-1}\mathbf{W}^T)^{-1} \quad (2.15)$$

provides a general solution to equation (2.14) [81, 162, 195, 204]. Therein, the weighting matrix \mathbf{P} allows for different weightings of the involved degrees of freedom causing a non-equal load distribution between the manipulators. In Hsu [81], Schneider and Cannon Jr. [162], different approaches of choosing \mathbf{P} and designing it dynamically changing (over time or as function of any other meaningful variable) are discussed to realize different

load-sharing ratios between the interacting partners, but they are not applied in a control design.

In the special case of \mathbf{P} being the identity matrix, the **Moore-Penrose pseudoinverse** is obtained

$$\hat{\mathbf{W}}^+ = \mathbf{W}^T(\mathbf{W}\mathbf{W}^T)^{-1} \quad (2.16)$$

leading to an equal load distribution on each degree of freedom. The degrees of freedom are distributed on the interacting partners. This solution is applied by, e.g., Li et al. [111], Walker et al. [203], Williams and Khatib [213].

Another solution is presented in Uchiyama and Yamashita [195] for the special case where torques can be neglected, and only forces are applied by two manipulators:

$$\hat{\mathbf{W}}^+ = \begin{bmatrix} \mathbf{A} \\ (\mathbf{I}_n - \mathbf{A}) \end{bmatrix}. \quad (2.17)$$

Assuming \mathbf{A} is a N -dimensional diagonal matrix, it is further written

$$\mathbf{A} = \text{diag}[\alpha_1, \dots, \alpha_N], \text{ and} \quad (2.18)$$

$$\sum_{i=1}^N \alpha_i = 1 \quad (2.19)$$

where α_i could generally take on any value. Here, as $N = 2$, $\mathbf{A} = \text{diag}[\alpha_1, \alpha_2]$. In Zheng and Luh [223], it is nicely argued that under energy aspects, $\alpha_i \in [0; 1]$ should be set. Depending on the chosen value of α_i , this means that the i -th partner takes over between none ($\alpha_i = 0$) or all ($\alpha_i = 1$) of the load.

Once decided on a solution for \mathbf{W}^+ , the definition of the internal wrenches \mathbf{f}^i is still not unique. Any solution can be applied as long as it is in the nullspace of \mathbf{W} . If the generalized Moore-Penrose inverse is applied, the internal wrenches are commonly defined by its orthogonal projection into the nullspace

$$\hat{\mathbf{f}}^i = \begin{bmatrix} \mathbf{f}_1^i \\ \boldsymbol{\tau}_1^i \\ \mathbf{f}_2^i \\ \boldsymbol{\tau}_2^i \end{bmatrix} = (\mathbf{I} - \hat{\mathbf{W}}^+ \mathbf{W})\boldsymbol{\xi} \quad (2.20)$$

with $\boldsymbol{\xi}$ being an arbitrary constant. This approach is applied by, e.g., Kerr and Roth [99], Reed and Peshkin [148], Williams and Khatib [213]. Different task-sharing ratios can be realized between the partners by designing controllers with different values of $\boldsymbol{\xi}$. Similarly, in Lawitzky et al. [107] the effort-sharing parameter λ is introduced to control the effort sharing between human and robot.

However, in, e.g., Walker et al. [204] and Yoshikawa and Nagai [220], it is argued that, though mathematically correct, applying this solution for \mathbf{W}^+ and the straightforward

projection to the nullspace for the definition of the internal wrenches leads to physical inconsistencies. The explanation for these physical inconsistencies is the following: Although the internal wrenches (if defined by the projection in the nullspace of \mathbf{W}) have no contribution to the motion-causing external wrenches, the external wrenches contribute to the internal wrenches because of inertial forces. For a more detailed discussion of this topic, please, refer to, e.g., Montemayor and Wen [126], Schneider and Cannon Jr. [162], Tinós et al. [187], Walker et al. [204], Wen and Kreutz-Delgado [211].

To overcome this, one prerequisite to achieve that the external manipulation wrenches do not contribute to internal wrenches is shown in Walker et al. [204]: The pseudoinverse needs to have the form

$$\hat{\mathbf{W}}^+ = \begin{bmatrix} \mathbf{C}_1 & \mathbf{0}_3 \\ -\frac{1}{n}\mathbf{R}_1 & \mathbf{C}_1 \\ \vdots & \vdots \\ \mathbf{C}_n & \mathbf{0}_3 \\ -\frac{1}{n}\mathbf{R}_n & \mathbf{C}_n \end{bmatrix} \quad (2.21)$$

with the main characteristic of \mathbf{C}_i being a diagonal matrix, . It is further suggested to choose $\mathbf{C}_i = \frac{1}{N}\mathbf{I}_3 \quad \forall i = 1 \dots N$ where N is, again, the number of interaction points with the object.

Another, physically intuitive solution for manipulating and grasp forces in case of 1-dof translational forces that are applied by two manipulators on an object is presented by Yoshikawa and Nagai [220]. The extension to three manipulators applying forces in any direction on the object is discussed. This definition is successfully applied by Hsu [81].

Based on these considerations, one solution of the pseudoinverse and internal wrenches for a collaborating dyad is introduced in the following for 1-dof, translational motions. This is because the focus of this dissertation is on 1-dof object-manipulation scenarios as depicted in Fig. 2.3. In this case and assuming a rigid object which weight is compensated, only forces in x -direction can be applied by the partners, and equation (2.11) simplifies to

$$f_o(t) = m_o\ddot{x}_o(t) \quad (2.22)$$

in time domain. And, with respect to a later controller design,

$$Y(s) = \frac{\dot{X}_o(s)}{F_o(s)} = \frac{1}{m_o s} \quad (2.23)$$

in the Laplace domain.

The following conventions are made. It is spoken of an *acceleration of the object* if the absolute value of its velocity is increased, i.e., $\ddot{x}_o > 0$ if $\dot{x}_o \geq 0$, or $\ddot{x}_o < 0$ if $\dot{x}_o \leq 0$. Accordingly, it is referred to a deceleration of the object if the absolute value of the object's velocity is decreased, i.e., $\ddot{x}_o > 0$ if $\dot{x}_o < 0$, or $\ddot{x}_o < 0$ if $\dot{x}_o > 0$. This is contrasted to *positive/negative accelerations* which correspond here (1 dof in x -direction) to a positive

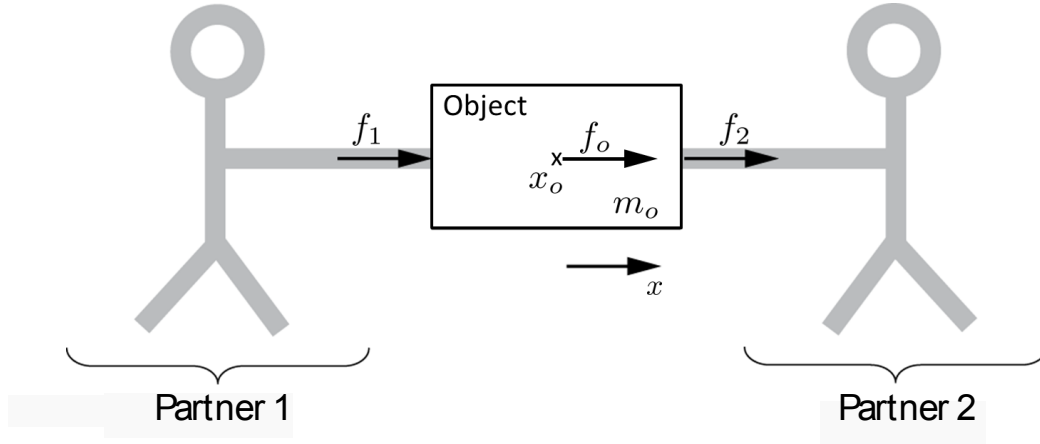


Fig. 2.3: 1-dof model of an interacting dyad in a joint object-manipulation tasks: The partners grasp the object rigidly and opposite of each other, such that no torques occur. Forces f_1 and f_2 can be applied by the partners in x -direction. This leads to the resulting force f_o causing object motion. x_o is the position of the object and m_o its mass. The weight of the object is compensated.

acceleration of the object to the right ($\ddot{x}_o > 0$) and a negative acceleration to the left ($\ddot{x}_o < 0$).

Due to the assumption of a rigid object represented by a point mass and the known location of the interaction points of the partners with the object, the motion variables of the object's center of mass are the same as the one's of the interaction point with the partner's end-effectors, i.e., $x_1 = x_2 = x_o$, $\dot{x}_1 = \dot{x}_2 = \dot{x}_o$ and $\ddot{x}_1 = \ddot{x}_2 = \ddot{x}_o$. Without loss of generality, partner 1 is assumed to grasp the object rigidly on the right and partner 2 on the left. For this reason, there are no grasp models depicted in Fig. 2.3, and the partners can apply forces (no torques), positive as well as negative, along the x -axis. The resulting force on the object is determined by

$$f_o = m_o \ddot{x}_o = f_1 + f_2 = \mathbf{W} \mathbf{f}. \quad (2.24)$$

with $\mathbf{W} = [1 \ 1]$.

As discussed above, the pseudoinverse of \mathbf{W} as well as the definition of the internal forces, is not unique. Here, the force decomposition into external and internal forces as introduced by Uchiyama and Yamashita [195], Yoshikawa and Nagai [220] is adopted fusing their lines of argument. Following Uchiyama and Yamashita [195], the inverse of $\mathbf{W} = [1 \ 1]$ is defined

$$\hat{\mathbf{W}}^+ = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ (1 - \alpha_1) \end{bmatrix} \quad (2.25)$$

with

$$\alpha_1 + \alpha_2 = 1, \quad (2.26)$$

$$\alpha_1 \in [0; 1], \quad (2.27)$$

$$\alpha_2 \in [0; 1]. \quad (2.28)$$

Unlike the Moore-Penrose pseudoinverse, this generalized solution enables an intuitive description of unequal workload sharing between the interacting partners.³

Next, to derive a definition of the internal forces, the nullspace property, i.e., $Ker(\mathbf{W}) = \{\mathbf{f} | \mathbf{W}\mathbf{f}^i = 0\}$ is addressed for the present case leading to

$$f_1^i + f_2^i = 0. \quad (2.29)$$

Hence, $f_1^i \equiv -f_2^i$ and $\begin{bmatrix} f_1^i \\ f_2^i \end{bmatrix} = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \hat{f}^i$. Based on this, the internal force \hat{f}^i is defined similar to Yoshikawa and Nagai [220]

$$\hat{f}^i = \begin{cases} f_1 & \text{if } \text{sgn}(f_1) \neq \text{sgn}(f_2) \wedge |f_1| \leq |f_2| \\ 0 & \text{if } \text{sgn}(f_1) = \text{sgn}(f_2) \\ -f_2 & \text{if } \text{sgn}(f_1) \neq \text{sgn}(f_2) \wedge |f_1| > |f_2|. \end{cases} \quad (2.30)$$

Based on the here-made assumptions, the partners pull away from each other if $\hat{f}^i > 0$, and they push against each other if $\hat{f}^i < 0$. As this definition is the only one applied throughout the rest of this dissertation, the $\hat{\cdot}$ is dropped. The difference to Yoshikawa and Nagai [220] leading to a small modification of the definition is that, here, partners can push and pull, whereas in Yoshikawa and Nagai [220], the partners can only push against each other.

Applying those definitions and if $f_o \neq 0$,

$$\alpha_1 = \frac{f_1 - f^i}{f_o} = \begin{cases} 0 & \text{if } \text{sgn}(f_1) \neq \text{sgn}(f_2) \wedge |f_1| \leq |f_2| \\ \frac{f_1}{f_1 + f_2} & \text{if } \text{sgn}(f_1) = \text{sgn}(f_2) \\ 1 & \text{if } \text{sgn}(f_1) \neq \text{sgn}(f_2) \wedge |f_1| > |f_2|. \end{cases} \quad (2.31)$$

Hence, α_1 is a function of f_1 and f_2 . If $f_o = 0$, then, either $f_1 = -f_2$ (and, thus, $\alpha_1 = 0$) or $f_1 = f_2 = 0$. In the latter case, there are no forces applied by the partners and, thus, it is defined $\alpha_1 = \alpha_2 = 0$.

In summary, a physically intuitive definition of external and internal forces is presented for a 1-dof, collaborative object-manipulation task. Unequal workload sharing can be described by the model and is directly determined from $\hat{\mathbf{W}}^+$ in (2.25). Each partner's applied force is composed by the resulting force f_o causing the object motion $f_o = f_1 + f_2 = m_o \ddot{x}_o$, the

³It can be shown that $\hat{\mathbf{W}}^+$ is a *general inverse*, i.e., $A\hat{\mathbf{W}}^+A = A$, see, e.g., [11].

workload-sharing parameter α_1 and the internal force f^i

$$\begin{bmatrix} f_1 \\ f_2 \end{bmatrix} = \begin{bmatrix} \alpha_1 f_o + f^i \\ (1 - \alpha_1) f_o - f^i \end{bmatrix} \quad (2.32)$$

$$= \begin{bmatrix} f_1^e + f^i \\ f_2^e - f^i \end{bmatrix}. \quad (2.33)$$

The task execution as well as the interaction behavior of the dyad is completely described by f_o , α_1 and f^i ; in the following referred to as the “*interaction state*”.

In summary, this representation of the physical state of the interaction is chosen for the following reasons:

- A more intuitive interpretation of the interaction is enabled than by dealing with the applied forces.
- The workload-sharing parameter α_1 is complementary.
- The solution is physically consistent. The internal force f^i has no effect on the resulting forces f_o causing the motion of the object and vice versa.

2.3 Discussion

There are multiple ways to describe the dynamics of an object being manipulated by an interacting dyad. By fusing existing work, a dynamic, physical model is derived particularly suited for the given scenario of haptic, dyadic interaction. In general, models allow for an analysis of the plant characteristics to enable a systematic controller design. Thus, the model of the object dynamics is discussed with respect to the design of haptic interaction controllers in the following. First, physically feasible *interaction states* are identified. Next, control variables and the control to feasible states in robot-robot as well as human-robot interaction are examined.

2.3.1 Feasible interaction states

Referring to equations (2.30) to (2.31), the internal force and the workload-sharing parameter are defined piecewise linear/constant on the same intervals. If one variable depends linearly on f_1 or f_2 , the other is constant and vice versa. This is illustrated in Fig. 2.4 by a grid of the interaction state as a function of the applied forces f_1 and f_2 . This shows that in this state space not all states are feasible. This result is of major importance for a control design that enables robots to collaborate with humans in a joint object-manipulation task. Because, even if required for successful task execution, the interaction dynamics cannot be controlled to any arbitrary interaction state, in particular not to any combination of internal force and workload sharing between human and robot.

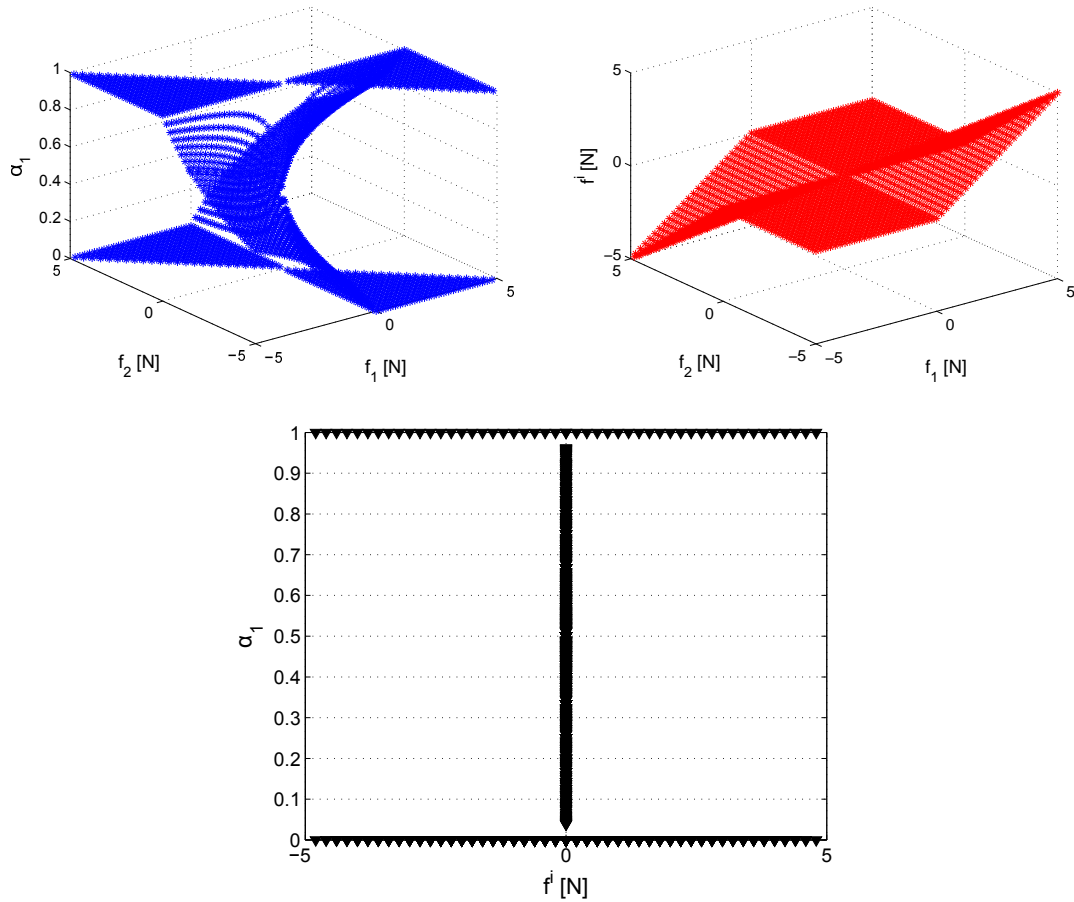


Fig. 2.4: Grid of workload-sharing parameter α_1 (upper left) and internal force f^i (upper right) as a function of the applied forces f_1 and f_2 , cf. equations (2.30) to (2.31); f_1 and f_2 are incremented from $-5 N$ to $5 N$ in $0.2 N$ steps. By this, the feasible interaction states are illustrated: Though not explicitly plotted, f_o can take on any value (with respect to the grid interval). But,
 $\alpha_1 \in \{0, 1\}$ if $f^i \neq 0$ or, by definition, if $f_1 = f_2 = 0$.
 $\alpha_1 \in [0, 1]$ if $f^i = 0$.
 Thus, not all combinations of f^i and α_1 are feasible as illustrated by the lower, center plot.

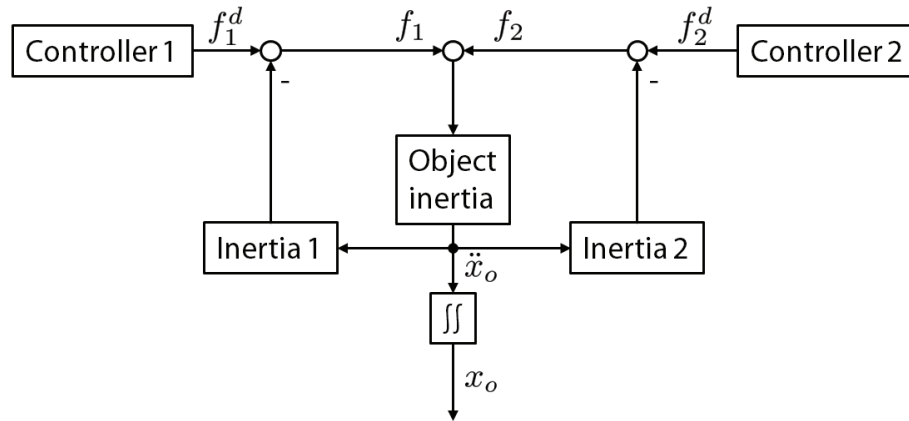


Fig. 2.5: Block diagram of the coupled dynamics of the closed kinematic chain formed by partner 1 and partner 2: Their forces f_1 and f_2 applied at the interaction points are a combination of each partner's planned control action (in form of the desired force f^d) and the reaction of their coupled inertias on the applied force $f_o = f_1 + f_2$: $f_1 = f_1^d - m_1 \ddot{x}_o$ with f_1^d the desired control force of partner 1, m_1 the inertia of partner 1, \ddot{x}_o the object's acceleration and f_1 the applied force of partner 1.

2.3.2 Towards controller design

Control system

If two partners interact haptically in a joint object-manipulation task, a physical link is established between them. They form a closed kinematic chain and a closed-loop control system. In general, the partners act as two controllers aiming at their individual control objectives. As haptic collaboration is addressed, the previously-introduced assumption is applied: The interaction partners have a shared, high-level goal⁴, e.g., a desired trajectory of the object. Based on this and feedback received from the environment, they plan their individual control actions which are applied to the object simultaneously causing task execution.

Though one could consider different control variables, these are commonly the forces applied by the interacting partners. Hereby, the closed kinematic chain and the resulting coupled dynamics of the interacting partners' mechanical impedances and the one of the object have to be considered. Thus, the applied forces are a combination of a force planned to be applied by each partner and the influence of the coupled dynamics as illustrated in Fig. 2.5. For the sake of convenience, the impedances are depicted as inertias-only in this figure. In general, the mechanical impedance of the human arm or the object (lumped element models) is characterized by its inertia m , its damping b and its stiffness described by the spring constant k . If the coupled dynamics are known, they can be considered explicitly in the controller design. If not, the control behavior has to be robust against them or compensate for them in a feedback loop.

⁴It may vary to some extent due to different perceptual systems.

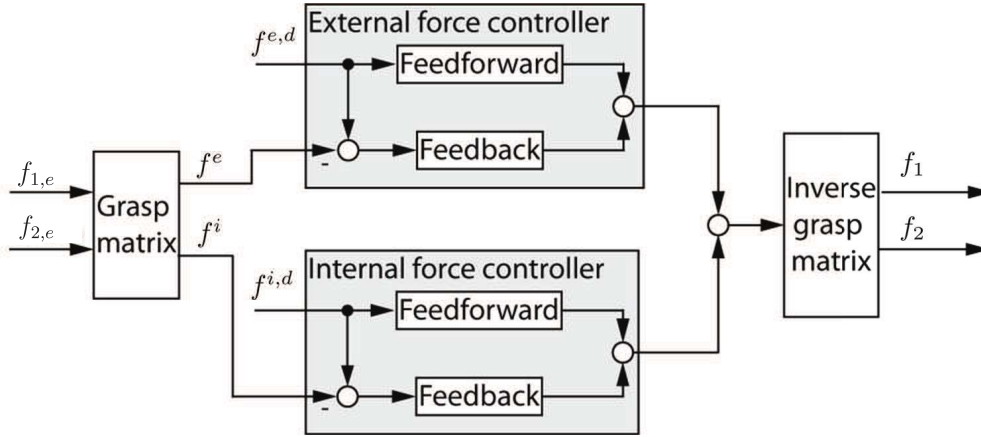


Fig. 2.6: Typical example of a controller for independent external-force control and internal-force control: Based on the grasp matrix and the measured applied forces $f_{1,e}$ and $f_{2,e}$, the current internal and external forces, f^i and f^e , are determined. These serve as input for the internal-force controller and external-force controllers which require also the respective reference values $f^{i,d}$ and $f^{e,d}$. Their outputs are transformed by applying the inverse grasp matrix to obtain the control actions in form of the applied forces f_1 and f_2 .

Control to feasible interaction state

The interaction state consists of the workload-sharing parameter α_1 , the internal and the resulting forces. For a general robot-controller design either in dyadic robot-robot or human-robot object manipulation, the question arises if the robot is able to control these three variables to any feasible reference state or trajectory (as a temporal sequence of states) in order to achieve a desired interaction behavior. This is closely related to controllability: a linear system is *controllable* if there is “the possibility of transferring any initial state to zero by a suitable control action”⁵ [93].

The workload-sharing parameter and the internal and resulting forces are described by non-linear dynamics. For this reason, classic controllability criteria cannot be applied. However, for a general discussion, results obtained in literature based on linearizations are used in the following. The idea behind controllability is adopted and applied in extreme cases. It is further distinguished between robot-robot and human-robot interaction. First, the case of two robotic partners solving a joint object-manipulation task is addressed. It is assumed that both robots are equipped with force and position sensors, and that this information is available to all involved controllers such that feedback control is possible for each robot. In a next step, the implications of having a human collaborating with a robot instead of two interacting robots are discussed.⁶

⁵Controllability is defined for linear systems only. In case of non-linear systems, it is extended to *flatness*.

⁶If one of the robots is not equipped with force and position sensors or if each robot has only information about its own applied forces, a line of argument similar to the human-robot collaboration case can be taken.

Haptic robot-robot interaction: Exploiting that the internal forces lie in the nullspace of the manipulation forces, a common approach in the coordinative control of multiple robots is the independent control of internal and external forces. By this, the simultaneous control to a desired motion of the object and internal loading is achieved, cf., e.g., [143]. The workload-sharing ratio is usually kept constant during task execution [81, 104, 162, 223], but some researchers realized coordinative robot controllers with dynamically changing workload sharing [81, 162]. A typical structure of such a coordinative controller is depicted in Fig. 2.6. In Hsu [81], it is also shown that if both applied forces are controlled by robots, any feasible interaction state, i.e., any feasible combination of workload sharing, internal force and resulting force, can be set.

Haptic human-robot interaction: Next, the case of human-robot interaction is considered. Here, only one control input is provided by the robot and the other one by the human. In a control sense and from the point of view of the technical system, the forces applied by the human are an *uncontrollable input*⁷. In Lewis and Murray [110], the controllability of the object’s motion in a dyadic, 2-dof, human-robot object-manipulation task was shown for one 2-dof control input and the unconstrained case, i.e., with no external constraints like obstacles. This means that, in spite of the unknown human input, the robot can control the object’s motion trajectory along any desired reference. However, only the controllability of the object’s motion is addressed, and, as not relevant in their work, workload sharing and internal forces are not considered.

However, considering feasible interaction states, the robot can control at most two of the three variables to a desired value⁸. To demonstrate this, consider the following two, rather abstract, but illustrative, examples. Without loss of generality, the index 1 is assigned to the robot partner and the index 2 to the human partner:

1. A robot is usually introduced in object-manipulation tasks to assist the human partner in task execution and to support task performance. Assuming that the robot has perfect task knowledge, it aims at taking over the whole workload, i.e., $\alpha_1 = 1$. Hence, the robot executes the task autonomously, and any force applied by the human should be compensated for by the robot’s controller. As α_1 is set constant and $f_1^e = f_o$ is only task related, any force applied by the human is “transformed” into an internal force by the robot (similar to Lawitzky et al. [107]). This means that a) the human partner has no influence on task execution anymore although he or she puts effort into the task by applying forces, and b) the internal forces are determined by the forces applied by the human and cannot be controlled by the robot to a desired value.
2. If the robot aims at controlling to a workload-sharing parameter different from 0 or 1, the internal forces have to be 0. Hence, an internal-force controller realizing $f^{i,d} = 0$ has to be implemented on the robot. Then, every force applied by the human is an external one because $f_2 = \alpha_2 f_o$. Further, assume that the robot, again, aims at perfect task execution with $f_o = f_o^d$. To achieve this, α_1 of the robot has to be dynamically

⁷Some authors refer to an uncontrollable input as a disturbance.

⁸In current literature, the control (and controllability) of two of these variables is typically approached [107, 216], and the third variable is not addressed.

changing and cannot be controlled to a desired reference value. And, if the human applies a force that is greater than f_o^d , the robot cannot compensate for this without building up internal forces.

In summary, these two examples and the assessment of the feasible interaction states in the preceding paragraph point out the limitations of control to a desired interaction state by technical partners in haptic human-robot interaction. And, consequently, the importance of their careful definition.

2.3.3 Extension to multiple degrees of freedom

The established model applies to 1-dof scenarios because these are in the focus of this dissertation. However, an extension of the presented solution of \mathbf{W}^+ and the internal wrenches to multi-degrees-of-freedom tasks is straightforward. This is because all of the literature, this model is based on [195, 204, 220], presents multi-dof approaches. Similarly, all the control strategies discussed can be applied in multi-dof scenarios.

The generalization of the results obtained in the previous paragraphs of this discussion on feasible interaction states is more complex. To enable a conclusion on this, the respective multi-dof model equations have to be set up and analyzed likewise as part of future research.

2.4 Conclusion

In this chapter, a physical model of the object dynamics in a dyadic, haptic, joint object-manipulation task is presented based on related work. Due to redundancy, there are multiple solutions. Different solutions are discussed, and by fusing existing approaches, **one solution for the 1-dof case is derived specific to dyadic, haptic interaction.**

This solution broadens the focus from object motion and the forces causing object motion to the interaction between the partners. The object dynamics and the interaction between the partners is completely described by the resulting force f_o causing the object motion ($f_o = f_1 + f_2 = m_o \ddot{x}_o$), the workload-sharing parameter α_1 and the internal force f^i built up between the partners. They are combined in the interaction state. The external force of each partner, i.e., each partner's contribution to object motion, is determined by $f_1^e = \alpha_1 f_o$ and $f_2^e = \alpha_2 f_o = (1 - \alpha_1) f_o$, respectively.

One strength of this solution is that the workload-sharing parameters α_1 and α_2 are complementary. Further, it allows unequal, dynamically changing workload distributions between the partners as they are assumed to occur in haptic human-robot collaboration. In summary, these variables allow a **more intuitive representation and, thus, control of the interaction** between the partners than the applied forces f_1 and f_2 .

In the derivation of the model, it was ensured that the solution is **physically consistent**. The internal force f^i has no effect on the resulting forces f_o causing the object motion and vice versa. For the multi-dof case, the effect of inertial forces, often neglected in other modeling approaches, is discussed. In the special 1-dof case, the model assumptions are chosen such that inertial forces do not influence the internal forces.

It is shown that **not all states of this interaction state space are physically feasible**. Based on a typical control structure, it is further discussed that in robot-robot interaction any feasible interaction state can be achieved by appropriate control strategies. However, this is not the case in human-robot interaction. Above that, if not supported by the human partner, the robot-alone cannot control all three values of the interaction state to a desired, feasible reference value. Hence, in a robot controller design, the control objectives have to be defined carefully by choosing feasible values of the reference states. In addition, a prioritization of the control objectives is usually necessary.

It is discussed that the presented model, the definition of internal forces and the addressed control structures are already valid for or can be easily extended to multi-degrees-of-freedom scenarios. However, the extension of the conclusions on feasible interaction states and their control to multi-dof tasks is not straightforward and has to be part of future work. The procedure presented in this chapter serves as a first guideline to approach this challenge.

In summary, these findings demonstrate that the transfer of solutions from, e.g., haptic robot-robot interaction or interaction with passive environments to haptic human-robot collaboration is not sufficient. New means and methods have to be derived and established.

As a next step, control objectives in haptic collaboration are identified and defined in the following chapter. Further, a generic control framework is introduced that enables, in combination with the dynamic model presented in this chapter, a systematic controller design.

Finally, it has to be noted that this dynamic, physical model contributes not only to the design of robot controllers but also enables a deeper understanding of human, haptic collaboration behavior, cf. chapter 4.

3 Collaborative robot partners: Control objectives & control framework

In the previous chapter, the focus was on the definition of a physical model that describes the dynamics in collaborative object-manipulation tasks. This enabled an analysis and discussion of the plant dynamics, i.e., the object dynamics, to be controlled. Now, the focus is shifted from the object and interaction dynamics to the actual robot controller, cf. Fig. 3.1.

The control objective of existing interactive control approaches is usually successful task execution, typically aiming at high task performance. In collaborative tasks, task execution benefits from the cooperation of the interacting partners. Thus, the partners' control goal is not only high task performance but also their interaction with each other¹. Hence, new, collaboration-related control objectives have to be identified. They play a crucial role in the controller design because the robot's desired behavior is determined by them. In the following, **control objectives for robots in collaborative object-manipulation tasks** are identified. Realizing human-like behavior as an instance of intuitive interaction behavior as well as the weighting of different control objectives relative to each other is discussed.

In the second part of the chapter, a **novel, generic control framework**² describing a general control architecture is introduced serving as another ingredient for a successful controller design process. The definition of a control framework becomes the more impor-

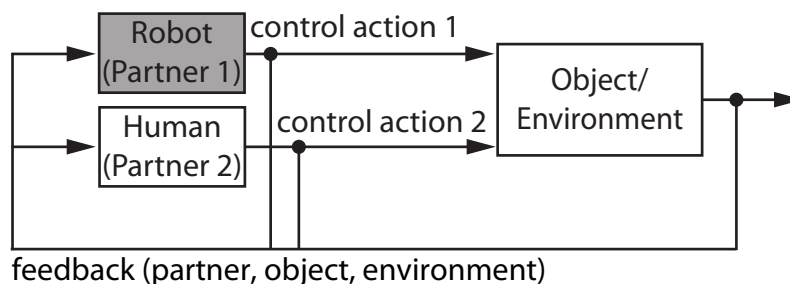


Fig. 3.1: Collaborating partners, human and robot, in closed-loop dyadic object manipulation: The focus of this chapter is on a robot control architecture enabling intuitive collaboration behavior.

¹Please note already at this point that task performance and interaction with the partner are generally not independent of each other.

²In Massink and Faconti [116], it is distinguished between *frameworks* (= *reference models*) and *formal models*. The latter ones are referred to as models in the following.

tant the more complex the considered system and the desired control behavior is. The new control framework is grounded in the framework presented by Groten [65] adopting the underlying requirements and a similar structure. Some modifications are required because the focus of Groten [65] is on the description of human behavior by control methods that are transferred to an artificial collaboration partner in a future step. Here, the focus is on the design of a robot controller. For this reason, a stricter separation between control and information-processing approaches, similar to the idea of Johannsen and Averbukh [91], is made, and one distinct control loop is defined.

By defining the structure of a system, a framework “*leads to a modular structure allowing for the inclusion of sub-models of limited scope that have been developed and validated separately*” [8]. It provides means to **integrate the current state of the art** (studies and models). A classification of the relevant literature based on the framework’s different subsystems is presented for the first time. This enables the identification of open challenge and leads to new conclusions. Furthermore, the applicability of models established in related fields of research like robot control in the context of haptic human-robot collaboration is approached.

Last but not least, a systematic and modular design approach of future systems is enabled by the control framework. It forms the basis for the design of human-like, robotic, haptic collaboration partners.

3.1 Control objectives in collaborative, haptic interaction

Within the control design for interactive, haptic, technical partners, the definition of *control objectives* is a key step. Thereby, control objectives are commonly formulated on a high-level as a desired behavior. Then, they are refined with respect to the chosen control strategy and the measures, reference trajectories or cost functions required to implement the control strategy. Typical control objectives aim at the minimization/ maximization of certain goals like task performance. In the following, control objectives and examples of control strategies characteristic for haptic collaboration are introduced and discussed.

3.1.1 Task performance

Most robots in human-robot interaction, in particular in object-manipulation tasks, are introduced to assist the human in task execution such that task performance is increased. Hence, most interactive robots control the task error to a minimum.

The main challenge in this context is the definition of appropriate task-performance measures. Task-performance measures are highly task-dependent and, thus, relate to requirements made on task execution. Therefore, ideal task execution has to be defined as a reference first. It is usually described in form of motion trajectories or force profiles.

In most object-manipulation tasks, the focus of task execution is either on speed or accuracy. This is illustrated by the following example: Consider two humans carrying a bulky furniture in a narrow staircase. To avoid damage of the wall, the humans would carry the object carefully, i.e., with high accuracy and small speed. However, if the furniture was carried in open space, the humans would carry it probably as fast as possible to reduce their effort. Here, speed is more important than accuracy. Thus, different task-performance measures, one to approach speed and the other one to approach accuracy, would be applied in each of the two scenarios (or a different weighting of them).

In this context, typical (objective) task-performance measures

- addressing speed are, e.g., task completion time [9, 157, 198, 226];
- addressing accuracy are, e.g., failure rates [155], time on target/error-free time [9, 54] and task error [89, 225].

These examples of task-performance measures are typically position-/velocity- or time-based.

Usually, an analysis on the dyadic-level-only and not on each partner's individual level is enabled by these measures. For the analysis on an individual level, other methods have to be chosen. One approach is the usage of subjective measures, e.g., in form of questionnaires. This method is mainly applied in virtual-environment studies to evaluate perceived task performance in order to gain insight in latent psychological concepts [9, 92, 101, 132, 155, 157]. Although these measures provide data of each of the interacting partners, they still address the overall impression of haptic interaction. Only, measures like perceived individual task performance [157] address the characteristics of the individual's contribution to a collaborative task. However, the preliminary results of Sallnäs et al. [157] further show that objective task-completion time and a subjective task-performance measure are not statistically correlated. Still, in both measures task performance is significantly better in a visual-audio-haptic condition than in a visual-audio condition. This points to the reliability of subjective measures that is often difficult to assess. Furthermore, the rating of subjective measures is commonly conducted after the task was executed. This is another aspect why subjective measures are usually not applied for control strategies which rely on permanent feedback during task execution.

In classic control approaches, objective performance measures serve as basis for feedback controllers that aim at minimizing the difference between the desired and actual trajectory. This is applied, e.g., in robots providing virtual fixtures that guide the human to a desired reference trajectory. It is spoken of virtual fixtures if the robot introduces either passive constraints like virtual walls [6, 182] or active guidance [127, 138] in order to reduce the user's workload and to improve task performance. Virtual fixtures are realized, e.g., in form of force fields along a desired trajectory.

However, task performance can only be the robot’s control objective if it knows the task goal and how to achieve it. This leads to a classic discrepancy of haptic assistant research: Assuming the technical partner has perfect task knowledge, the most efficient approach would be either

- a) to replace the human by an autonomous system, or
- b) to give the robot full control over task execution. If the human still applies forces, they would be “transformed” to internal forces not contributing to object motion. Such a control strategy can be realized by, e.g., the approach presented by Lawitzky et al. [107], Oguz et al. [133] if the parameters are chosen accordingly.

However, if the robot does not know the task, it can hardly contribute efficiently to task execution. One way to approach this challenge is to introduce assistance levels based on the current task knowledge [122]. The more certain the robot is about task execution, the higher its contribution to it.

3.1.2 Cooperation & coordination

Another control objective is “good” cooperation. It focuses on the quality of the interaction between the partners. The main challenge is the definition of “good” in this context as the following discussion shows.

In literature, cooperation measures either evaluate the similarity of the force inputs of the collaborating dyad [58, 141] or the energies exchanged between the partners [84, 114]. In Passenberg et al. [141], a force-based cooperation measure evaluating internal forces is successfully applied to evaluate the *degree of agreement* between a human user and a technical assistance function. There, the degree of agreement resembles one instance of the quality of cooperation.

Most other approaches that address the degree of cooperation are related to the effort applied by each partner. *Effort* refers to the physical as well as cognitive load exhibited by the human during task execution. Assuming a constant effort for task execution, effort is closely related to (work-)load sharing, i.e., the ratio of each partner’s individual effort. Cognitive load or mental effort corresponds to the “*total amount of controlled cognitive processing in which a subject is engaged*” [137]. In the following, the focus is on physical effort described by forces and energies.³ The technical partner’s effort is subject of many classic robot control approaches. In the context of haptic human-robot interaction, the effort applied by the human is brought in focus. This is because a technical partner is commonly introduced to assist and relieve the human.

³For a more detailed discussion on effort in dyadic, haptic human-robot collaboration please refer to Groten et al. [231, 232].

In Ikeura et al. [84], energies are analyzed in an object-carrying task where one human is the leader initiating the motion, and the other one is a passive follower. Two different measures for *cooperation efficiency* are suggested:

- the energy exchange between the object and the slave E_s and
- $J(t) = \int_0^t \ddot{E}_s^2 dt$;

Applying the first measure, the coordination is rated the better the more passive the follower behaves. The second measure describes “*how smoothly the energy flows into the follower*” [84]. Because of this and because some literature suggests that humans prefer smooth motions minimizing jerk [46], the second measure is to be preferred. A similar measure is applied by Lawitzky et al. [107], Maeda et al. [114].

If the technical partner aims at improving cooperation by minimizing the total effort or the human effort, it is generally referred to as *coordination control*. One instance to achieve this control goal is the minimization of the forces applied by the human. If perfect control behavior was possible, moving an object would feel like free-space motion to the human. If this control strategy is applied, the robot generally requires no task knowledge and aims to be a pure follower.⁴ One main limitation of this approach is that the robot is not able to express own intentions. This means it cannot improve task execution with potentially available task knowledge.

Another instance of coordination controllers are internal-force controllers. Commonly, the internal forces are controlled to 0. Thus, the human effort is reduced by the internal forces usually present in haptic interaction. And, all of the human partner’s applied forces result in object motion. As an instance, this is realized in Griffin et al. [62], Rahman et al. [145]. Again, the robot does not require any task knowledge and cannot contribute actively to achieve the task goal.

One other coordination objective is to control the human’s workload either to a statically or dynamically changing reference value. If workload sharing is addressed in the current literature, a desired value is determined and applied, but it is commonly not controlled. In case of deviations, no corrective actions are taken, cf., e.g., [25].

The fact that most of the presented control strategies for cooperation or coordination do not require any task knowledge, highlights the focus of these control objectives on the interaction between the partners rather than the actual task or how the task is executed.

⁴The following has to be noted: Jarrasse et al. [90] showed that human effort can be further minimized by adding task knowledge in a feedforward branch of the control such that the human behavior can be predicted.

3.1.3 Haptic communication

Some literature suggests that the haptic channel serves as a mean of communication (maybe in combination with other modalities) enabling the interacting partners to exchange information and intentions with each other [234], e.g., to negotiate on a joint object trajectory or the role each partner takes on. Conveying such information might be another control objective of a collaborative, technical partner. To realize explicit haptic communication by a control strategy, the main prerequisite is that the robot has the respective task/collaboration knowledge that is to be exchanged and the respective cognitive capabilities to interpret it.

Within the field of haptic communication, it has to be distinguished between artificial haptic cues [113, 132] and natural haptic communication [41, 148, 149, 233, 234]. *Natural* haptic communication commonly refers to human-like communication. In this case, dynamic internal forces are suggested as communication channel [148]. However, no *haptic language* or *haptic alphabet* that could be implemented on a robot controller has been identified so far.

3.1.4 Discussion

In summary, control objectives in the context of haptic human-robot collaboration are mostly related to task performance, cooperation/coordination or haptic communication. By defining these control objectives and the respective control structure, the behavior of the robot, i.e., its interaction strategy and role, is determined. As an instance, consider a robot with a control that realizes a high workload-sharing parameter. It shows a very dominant behavior.

A key requirement in the design of a haptic, collaborative robot control is that the robot aims not only at supporting high-performance task execution but also at enabling intuitive interaction with the human. Controllers have to be defined that enable the control of objectives related to both of these aspects. Thus, if real haptic collaboration is to be achieved, multiple control objectives have to be taken into account in the controller design. When defining them explicitly for a certain use case, the following two important points have to be considered:

1. Control objectives can be contradictory: Coordination controllers aim at minimizing the human effort, e.g., the internal forces. In contrast, with respect to haptic communication, there is the following, generally-accepted hypothesis: Haptic effort (to be more precise, the energy exchange between the partners or the internal forces built up) is important in haptic collaboration because it serves as a mean of communication required for intention negotiation [41, 149, 232].

2. Control objectives can be dependent: As an instance, increased task performance achieved by a faster task execution or shorter trajectory commonly results in a reduced human effort.

Thus, the feasibility of all control objectives as well as their reachability in human-robot collaboration have to be guaranteed. Furthermore, different context-specific weights can be put on the control objectives in order to obtain a prioritization of them. This is illustrated by the following two scenarios: As the robot is usually introduced to enable increased task performance, the main control objective is typically related to a desired object trajectory and the resulting force. The control of the interaction with the partner is rather subordinate then. However, if the robot has no task knowledge, controlling the interaction with the human is in the focus, e.g., to follow or to communicate haptically in order to obtain the required task information from the partner.

Some authors presenting interactive controllers claim to enable “intuitive” human-robot collaboration, cf., e.g., [133]. However, commonly task performance is controlled, and no further discussion of the control objectives and strategies that lead to the robot’s “intuitive” interaction behavior is presented. This dissertation aims to close this gap by establishing human-like interaction behavior as one instance of intuitive, haptic interaction. In more detail, the goal is to achieve human-like interaction behavior of technical partners rather than rebuilding the human neurologic and sensorimotor control loops. It is emphasized that “intuitive or human-like interaction behavior” is not classified as a separate control objective. It is rather a manifestation of a control objective than a control objective itself, e.g., human-like task performance or human-like cooperation.

Within the controller, the control objectives are achieved by influencing the involved control variables. In the present context, this typically involves haptic variables of motion (position, velocity, acceleration) and forces (applied, external, internal, resulting) or workload sharing. The defined control objectives have a direct influence on the controller structure as they determine the controlled variables and the characteristics of the controlled behavior. Thus, the definition of the control objectives and of their related measures or trajectories has to be conducted before the actual controller design.

In chapter 2, a dynamic object model adapted to haptic interaction is introduced. It distinguishes the resulting force causing object motion and the rather interaction-related variables of internal forces and workload sharing. It is important to note that there is no unique assignment of the above-introduced control objectives to these variables. As an instance, the control goal of intuitive interaction behavior can be realized by planning a human-like object trajectory or a controller realizing human-like error-correction behavior.

In the context of this dissertation, in particular for the definition of the subsequently introduced control framework, it is assumed that the control objectives are described in terms of reference values of either of the variables position, velocity, acceleration, workload sharing, internal force, external force or resulting force.

3.2 Control framework

Based on related work, a generic control framework is introduced in the following. It allows the modular integration of different models that can be identified and developed separately. This approach is necessary due to the complexity of collaborative control in haptic human-robot interaction.

For the design and systematic development of interactive systems, different frameworks describing continuous interaction were introduced (literature surveys in, e.g., Baron et al. [8], Groten [65], Massink and Faconti [116]). Therein, haptic interaction/collaboration is described at an abstract level aiming at a high generalizability. One of the main concerns is the definition and differentiation of subsystems as well as their relation to each other, usually considering the consistency with established control methods only to a limited extent. Neuroscience and motor control approaches as, e.g., presented by Stroeve [180], Wolpert et al. [217], aim at modeling the on-going processes within a human that result in a certain interaction behavior. They rather focus on the realistic description of these processes than a transferability and feasibility on robotic systems. Finally, most of the frameworks presented in literature, e.g., [91], focus on haptic interaction of humans with their environment that is mainly passive. Hence, these approaches do not take into account the characteristics of haptic collaboration with an equal partner.

Few frameworks addressing the challenges of haptic collaboration were introduced by Groten [65], Massink and Faconti [116], Wang et al. [209], Wolpert et al. [217]. In Groten [65], the focus is on the analysis and description of human behavior that is transferred to an artificial collaboration partner in a future step. In the following, the same requirements underlying this framework are taken as starting point, but a modified approach is presented shifting the focus from the description of human behavior to the design of robot controllers to realize human-like behavior.

3.2.1 Requirements

Requirements to be met by a haptic collaboration framework are identified in Groten [65] based on an extended literature survey focusing on studies that address human-human interaction behavior. As the control framework introduced in the following aims at realizing control strategies for human-like collaboration behavior, the same requirements are applicable and recited and adopted in the following:

1. **Feedback loops** have to build the basis of the framework: Feedback loops emulate the human action-perception loop and are, thus, of particular importance. To approach this, the application of control methods is a key instrument. In the main feedback loop, the current state of the environment, the partner and the interaction itself as well as the effect of taken actions are perceived by humans or measured by technical systems and compared to a desired behavior. If necessary, corrective actions are commanded to

assure a successful achievement of the intended task execution as well as the intended interaction behavior. This is a first difference to most of the framework literature considering feedback control of task execution only.

2. As object-manipulation tasks are in the focus, **goal-orientation** has to be considered by the framework: This is achieved by defining the desired behavior of the technical partner in form of reference values or trajectories taking into account the shared goal. This relates to the definition of the control objectives introduced in the previous section. So far, motion trajectories of the object are commonly planned and applied in joint object-manipulation tasks. But, applying this to haptic human-robot collaboration, the force components gain importance.
3. Several aspects are combined in another requirement in Groten [65]: A haptic collaboration framework has to enable “**shared decision-making and the adaptation to the partner**” [65], both “**closely related to intention negotiation**” [65].⁵ For intention negotiation, the robot has to **recognize the human’s intention** and **integrate** it with its own current intention by decision-making and adaptation processes.
4. **Mental/internal models form a knowledge base.** The idea of mental models was first introduced by Craik [27]. It refers to models of reality being formed in people’s mind and allowing the prediction of the system’s state and similar future events. This concept forms the basis of all cognitive systems and is widely accepted in cognitive science [152, 214, 217]. In haptic collaboration, mental models of the environment in general and, in particular, the object, the task, the partner and the interaction have to be considered. In robotics, knowledge bases are represented in form of stored dynamic models, neural networks or fuzzy logic.
5. The final requirement is the definition of **different abstraction levels of information-processing** [2, 91, 146, 163]. The framework of Rasmussen [146], see Fig. 3.2, focuses on the human role in man-machine interaction and describes the processes inside of humans leading to their interaction behavior. This human performance model distinguishes between different levels of behavior: *knowledge-, rule- and skill-based behavior*. Therein, low-level *signals* are exchanged on the skill-based level corresponding to the sensory-motor level. *Signs* are exchanged in the middle layer of the framework which consists of subroutines described by rules. On the highest, the knowledge-based level, *symbols* are received and identified. Based on their interpretation and in combination with the task goal, new actions are planned. This concept raised a lot of attention and was adopted in the description of human as well as robot, haptic interaction behavior. Based on these levels of information processing, the framework in Groten [65] is divided into the different levels automation (originally skills in Rasmussen’s work), adaptation (originally rules) and knowledge.

⁵For a definition of these concepts please refer to chapter 1.

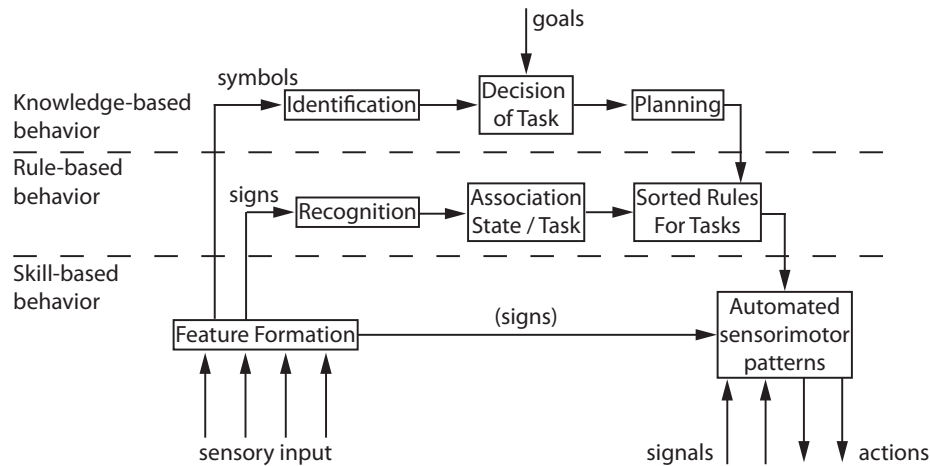


Fig. 3.2: The human performance model by Rasmussen [146]: It consists of different information-processing levels: skill-, rule- and knowledge-based behavior. The information is exchanged in form of signals, signs and symbols, respectively. Figure is redrawn from Rasmussen [146] ©1983 IEEE.

3.2.2 Introduction of framework

In this dissertation, a control framework as depicted in Fig. 3.3 is applied. It is similar to the structures presented by Groten [65], Johannsen and Averbukh [91], Rasmussen [146] and fuses their ideas focusing strictly on robot control in haptic collaboration. The idea of explicitly controlling the interaction strategy with the partner is added to enable collaborative robots in general and human-like, robot interaction behavior in particular.

According to the requirements discussed in the previous section, the control framework of a technical, haptic collaboration partner consists of the following components arranged on different levels of information processing: the *sensory* system, the *control* unit, the *motor* unit, the *intention negotiation* unit as well as the *knowledge base*, see Fig. 3.3.

These main components have distinct interfaces and exchange different types of signals and information:

- The main control loop consists of the sensory system, the interaction control as well as the motor unit inside the robot partner, and object and (human) partner as parts of the environment. There are *physical and control signals* (solid lines in Fig. 3.3) exchanged between them – in form of, e.g., measurement data, reference trajectories, control errors and control actions. The *perceived feedback* takes on a special role as it inputs not only to the main control loop but to all components. Perceived implies here that the feedback information from the environment is “filtered” and, thus, modified by the *sensory system*. The same information is perceived differently by each of the interaction partners.
- On the next information-processing level, intention negotiation takes places. The output of this subsystem are *negotiated individual intentions* (dashed lines in Fig. 3.3),

such as the negotiated shared task goal, individual action intentions or intended control strategies. These intentions are provided to the interaction control unit.

- The output of the knowledge base is *context-dependent information* (dot-and-dashed lines in Fig. 3.3) that serves to *adapt* the other components of the framework to the current situation. As an instance, parameter sets or adaptation rules may be provided to the respective subsystems.
- All components feedback information to the knowledge base (dotted lines in Fig. 3.3) such that it can be continuously *updated* and improved.

Going more into detail of the main components, the *knowledge base* contains the robot's stored information on tasks, environments, the partner's expected behavior and interaction strategies in form of system-theoretic models. It is continuously updated and extended by integrating new information, i.e., the robots *learns*.

The skill-based level of Rasmussen's framework is represented by the *interaction control unit* composed of an *interaction planner* and an *interaction controller*. The interaction planner receives feedback from the sensory unit as well as the negotiated shared goal from the intention negotiation unit and knowledge from the knowledge base. Based on this, a desired trajectory of the object as well as an interaction strategy are planned and output in form of a desired behavior. This desired behavior, the perceived feedback from the environment, individual intentions and information provided by the knowledge base feed the interaction controller. Based on this input, the robot's individual action plan is continuously determined. Thereby, the intentions as well as the context-dependent information determine the structure and parametrization of the interaction planner and interaction controller.

The robot's action plan is executed by the *motor unit* causing its (control) action. The execution of the desired actions is limited by the robot's *actuator* capabilities and affected by the coupled dynamics of the closed kinematic chain formed by the two interacting partners and the object. As the interaction control unit, the motor unit is adapted to the current situation and task based on knowledge provided by the knowledge base.

Finally, Rasmussen's rule-based level is adapted and modified such that *intention negotiation* takes place there. This unit consists of the two subsystems *intention recognition* and *intention integration*. Intention recognition means that based on perceived feedback and prior knowledge, the intention of the partner is estimated with respect to task and interaction plans. The estimated partner's intention and the robot's current own intention serve as input to the intention integration subsystem. There, the robot fuses continuously its own intention with the estimated intention of the partner starting with an initial intention provided by the knowledge base. This on-going intention integration requires adaptation as well as decision-making processes to achieve collaboration with the partner not leading to unresolvable conflicts. Thus, by integrating the negotiated intentions, the challenge to achieve compatible actions of the partners is addressed. More details on this process of intention integration are provided in the next section.

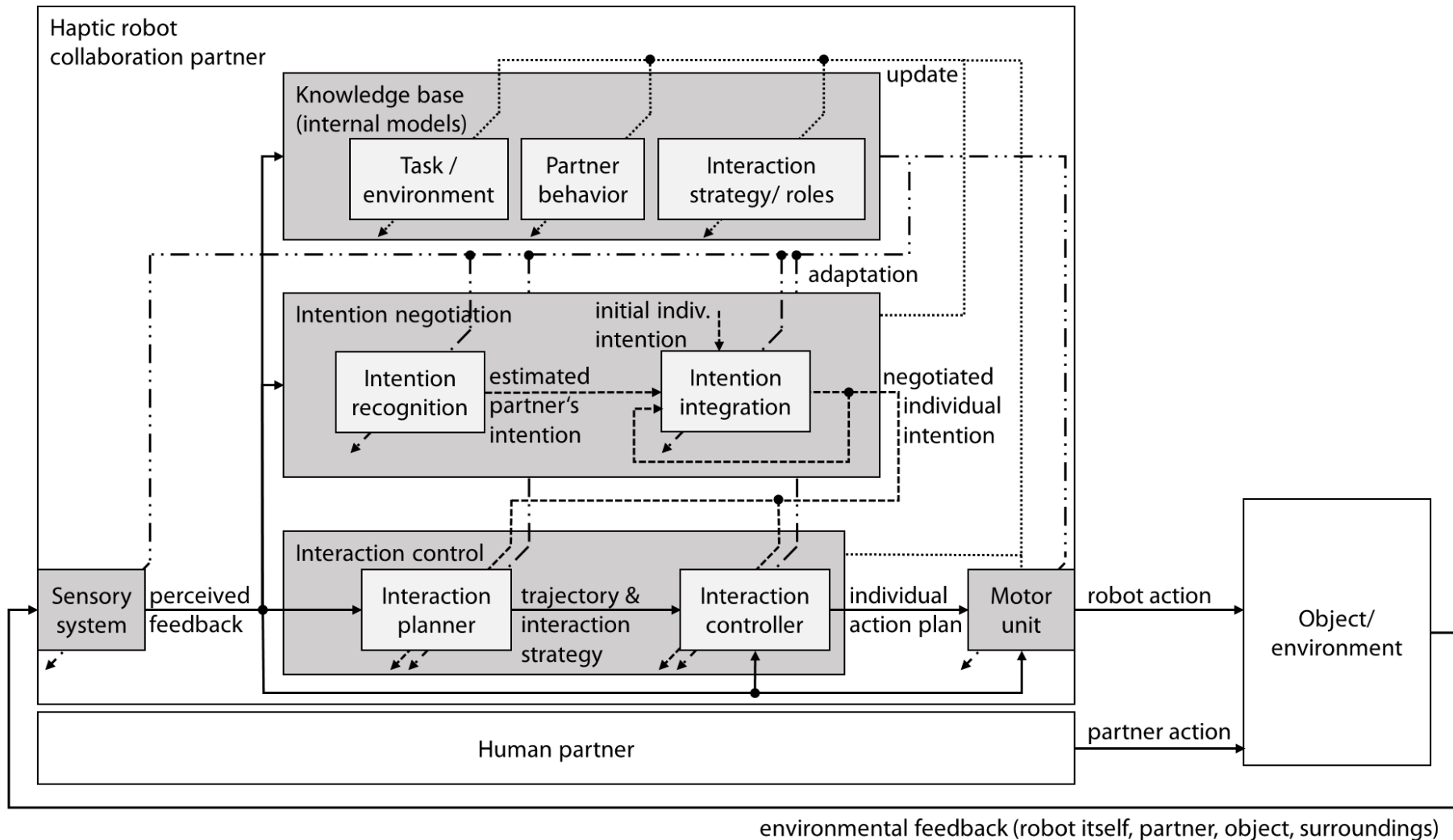


Fig. 3.3: Control framework of a collaborative, haptic robot executing an object-manipulation tasks in interaction with a partner; solid lines: control/physical signals, dashed lines: intentions, dot-and-dashed lines: information from knowledge base for adaptation, dotted lines: new information to update knowledge base

In summary, this novel control framework satisfies all the requirements identified in Groten [65] and reviewed here. For an application in haptic human-robot collaboration, the control of the interaction behavior with the partner is explicitly added by integrating an interaction controller and intention integration subsystem. This and the explicit definition of one main distinct control loop (consisting of the sensory system, the interaction control unit and the motor unit) upon which higher-level information-processing levels are set, distinguishes it from other frameworks. The latter allows the application of established control methods for the analysis of the closed-loop behavior.

However, according to Massink and Faconti [116], a framework *“on its own does not provide any specific technique or notation for the description of the behavioral aspects of interaction at the different layers of abstraction. It just provides a framework to guide the way in which a complex problem (...) could be split into sub-problems”* [116]. To complement these subsystems, models are required by introducing *“specific techniques”* [116], i.e., by applying adequate methods for each of the involved components.

To approach this challenge, state-of-the-art models are integrated into this control framework. Therefore, relevant literature of each of the framework’s subsystems is presented and discussed in the following. The focus is, thereby, on solutions incorporating human behavior characteristics in order to achieve human-like interaction behavior.

3.2.3 Integration with state of the art

Some authors [65, 103, 116] suggest and discuss different methods for realizing models within different modules of their frameworks. In Massink and Faconti [116], models belonging to the areas of manual control theory, hybrid automata, stochastic as well as UML-based approaches are suggested. The framework of Groten [65] discusses formal models for the different modules considering manual control theory, path planning and decision making. Körding and Wolpert [103], Wolpert et al. [217] relate motor control to social interaction and discuss Bayesian decision theory in sensorimotor control. However, all of these approaches focus on the description of human behavior and were not realized as control strategies on robotic systems.

On the other side, approaches in haptic human-robot interaction commonly rather apply a “bottom-up” approach where a control architecture is introduced that fits their present situation and specific task to be solved. As an instance, Solis et al. [176] define the subsystems of recognition system, control system and input/output device in the robot-assisted teaching of Japanese characters using a haptic interface. However, only task models are considered in a knowledge base. The following two examples are some of the few approaches enabling control of the interaction strategy. Both apply a two-level framework: In Wang et al. [209], the human’s intention in a handshake acting rather active or passive is estimated based on a static knowledge base. It serves as basis for the robot’s trajectory planner as well as a position-based admittance control generating the robot’s action. The hierarchical framework introduced by Lawitzky et al. [107] distinguishes the

two levels planning and control. However, intention integration or a knowledge base are not part of their framework, though prior knowledge about task execution is stored to enable robot control.

This list of examples could be further continued. But, these few examples already show that a) in most control architectures, some subsystems integrated in this framework are missing, and b) a transfer of the presented approaches to other tasks, specifications or scenarios is difficult to realize. As there is an information exchange between the different subsystems of the framework, a consistent structure of the models is important to realize the required interfaces. The “top-down”, generic framework presented in the previous section fills these gaps. Each of the subsystems and their relation to each other as well as their interfaces and the respective signals exchanged between them are defined. Thus, it allows a straightforward integration of existing models. Approaches from literature can be classified, generalized and, by this, potentially combined with each other and used in other applications. This is demonstrated by the following paragraphs. Further, new models (their structure and parameters) can be identified based on this control framework.

Sensory system

A technical partner perceives its surroundings by the sensors it is equipped with. In haptics, this refers usually to force as well as motion (position, velocity, acceleration) sensors. Every real sensor is subject to measurement errors caused by drift, noise or limited bandwidth. For this reason, the sensory subsystem contains typically low-level data processing, like anti-noise low-pass filters, calibration routines or offset compensation. Additionally, if applied in complex environments, the robot’s perception might be attention-driven, i.e., focusing on the main task neglecting other influences from the environment. Or, it is equipped with high-level perceptual skills including the identification and classification of its environment (e.g., obstacles, humans), cf., e.g., [14, 52].

The modeling and implementation of a human-like sensory systems on robots is challenging due to its very high complexity as, e.g., discussed in Coradeschi et al. [24]. The understanding and modeling of human perception is highly relevant in neuroscience for a deeper understanding of human capabilities, internal processes and behavior. However, a human-like perception system is of minor importance in haptic human-robot collaboration. This is because the robot’s behavior is expected to show human-like, hence, intuitive interaction characteristics, but, at the same time, the robot’s (control) capabilities are still to be exploited. As an instance, the usually broader bandwidth of a robot’s sensor compared to the human sensory system, enables a more distinct perception of the environment allowing a finer extraction of information.

Interaction planner

Every task has a goal that is aimed at. In haptic human-robot collaboration, it is assumed that the interacting partners have a shared goal that was successfully negotiated between the partners. This shared goal as well as perceived feedback information from the environment serves as input to the interaction planner. Within the planner, a desired trajectory or force profile and an interaction strategy are determined and output as desired behavior to the interaction controller.

The purpose of the interaction strategy planning is the determination of the interaction strategy itself, i.e., the structure of the interaction controller rather than the actual role, i.e., the controller's parametrization. So far, no explicit planning of an interaction strategy could be identified in the field of haptic human-robot interaction.

Most approaches presented in the literature and relevant for the interaction planner are on the planning of trajectories, in particular to describe free-space arm motions. Some approaches address the planning of a trajectory or force profile for the interaction point with an object or of two partners. An overview of this literature is given in the next paragraphs.

Timing constraints on point-to-point movements

There are attempts to transfer models describing free-space motion trajectories of the human arm to collaborative, human-robot object-carrying tasks. Then, the trajectories no longer describe the motion of the human arm but the desired, dynamic motion of the object. Such a model is *Fitts' law* [45] predicting the duration t_f of a human performing an aiming task at a target with width W over a distance D

$$t_f = a + b \log_2 \left(\frac{D}{W} \right) \quad (3.1)$$

where a and b are arbitrary constants.

In Reed et al. [147], Fitts' law was applied in a dyadic interaction task. It was shown that human dyads performed faster than individuals and that there was a weaker correlation of the model with the experimental data. A modification of Fitts' law, the Schmidt's law was addressed in Gentry et al. [54]. Like in Reed et al. [147], the model fit to the experimental data is lower for dyads than for individuals. Though it describes dyadic behavior to some extent, it has not been applied in human-robot collaboration yet. In this context, the finding of Desmurget et al. [29] has to be mentioned: They revealed that compliant (in interaction with a haptic interface) and unconstrained movements involve different planning strategies.

Motor-control-inspired trajectories

Another very well-known, task-specific model describing not only the duration of a reaching motion but also its dynamic trajectory is the *minimum-jerk* model [46]. The model is

based on the assumption that “a major goal of motor coordination is the production of the smoothest possible movement of the hand” [46]. This results in the objective function

$$J = \frac{1}{2} \int_0^{t_e} \left(\frac{d^3 x_1}{dt^3} \right)^2 + \left(\frac{d^3 x_2}{dt^3} \right)^2 dt \quad (3.2)$$

where t_e is the duration of the motion, and $\mathbf{x} = [x_1 \ x_2]^T$ is the 2-dimensional hand position in world coordinates. Widely used is the analytical solution to this optimization problem describing a hand motion with known duration, known start and final hand position \mathbf{x}_0 and \mathbf{x}_f :

$$\mathbf{x}(t) = \mathbf{x}_0 + (\mathbf{x}_f - \mathbf{x}_0)(15t^4 - 6t^5 - 10t^3). \quad (3.3)$$

The minimum-jerk model is now widely applied in robotics and has found several extensions like its application to continuous trajectories by defining via-points. In human-robot collaboration, it is applied for the generation of a desired object trajectory by, e.g., Corteville et al. [25], Maeda et al. [114]. However, it has to be noted that the minimum-jerk model was initially introduced for fast planar point-to-point motions. Thus, it is not surprising that Miossec and Kheddar [125] could not verify the minimum-jerk model for moving a handle-shaped object between two predefined locations on a table, neither for an individual nor for a dyad performing the task.

Other objective functions like the so-called 2/3-power law are suggested in literature to describe different human motor-control behaviors. An extensive overview and discussion can be found in Todorov [188]. Most approaches have not found significant application in real-time human-robot interaction yet due to the lack of experimental confirmation or the complexity of the objective functions requiring advanced optimization routines. One of the few exceptions is the minimum-torque-change model formulating smoothness optimization on the level of dynamics “by minimizing the time-derivative of joint torque” [188]: It was applied to describe human multi-joint arm movements [199] as well as for the trajectory generation of cooperating robots in an object-lifting task. Simmons and Demiris [173] discuss the minimum-jerk, the minimum-torque and the minimum-variance criterion for a human-inspired robot behavior. The minimum-variance criterion is then applied referring to it as the “most biologically realistic of the theories” [173]. Goncharenko et al. [60] state that, on a force level, movements can be predicted by a force-change-based criterion rather than by a force-based criterion. In this line, Ohta and Laboissière [134] found for a 1-dof crank-rotation task that the human behavior trajectories can be described as the result of a combined criterion minimizing the hand-contact-force change and the actuating-force change over the course of movement. Depending on the particular formulation of the respective objective functions, these approaches address the planning of trajectories or force profiles of the object or of the end-effectors.

Robot-inspired path planning

In general, trajectory or motion planning of mobile robots as well as of robots’ end-effectors or tools attached to them is a wide research field in robotics. It provides a large variety of

different planning methods. In highly-structured tasks like cyclical tasks (e.g., hand shakes [218] or dancing [78]), the derivation of the motion trajectory is straightforward based on task knowledge. Only few parameters like amplitude, frequency and phase are adjustable. In collaborative, haptic object-manipulation tasks, trajectory planning for the object (its center of mass) based on a given goal is more complex. The application of general path planning algorithms in this context as, e.g., realized by Lawitzky et al. [107] is effective for the generation of a desired object motion trajectory if the goal and some via-points are known.

The integration of the human behavior into the planner is highly challenging and usually not in the focus of classic planning algorithms.

Reproduction of learned human trajectories

The reproduction of previously learned (human) trajectories is another approach to plan task trajectories in order to realize human-like, haptic interaction behavior on a robot [20, 122]. In Calinon et al. [20], learning by demonstration was successfully applied to teach the robot two sets of stereotypically demonstrated scenarios for a 1-dof, collaborative lifting task. These correspond to two different role distributions among the human and robotic partner. Similarly, in Medina Hernandez et al. [122] a robot incrementally learned semantic task trajectories integrating the interaction behavior with the partner during execution of a joint-object carrying task using hierarchically-clustered Hidden Markov Models. In both references, these learned trajectories are, then, reproduced by the robot's control strategies. A common method in learning as well as the reproduction of learned trajectories are stochastic models like Hidden Markov Models (HMM) or Gaussian Mixture Models (GMM).

Interaction controller

The objective of the interaction control subsystem is to enable the robot to control task execution as well as the interaction with the partner towards a desired behavior. The desired behavior is provided by the interaction planner. Furthermore, feedback about the current state of the environment is also input to the interaction controller.

In general, the interaction controller can have any arbitrary but suited control structure composed of feedback and/or feedforward branches. In different research areas, approaches relevant for the definition of a general interaction control structure are presented and summarized in the following.

Feedforward controllers for execution of task and interaction strategy

Feedforward controllers aim at executing a desired trajectory without considering feedback of the actually executed behavior. In robotics, feedforward control branches commonly integrate the inverse dynamics of the robot in order to map the desired trajectory to the joint-space of the robot. They are applied mostly in combination with a feedback control

that compensates for the remaining control errors. In the context of haptic human-robot interaction, this is applied, e.g., by Lawitzky et al. [107], Oguz et al. [133]. A purely feedforward-type controller is applied by Reed and Peshkin [148]. There, interaction strategies were identified in human-human interaction. Based on this, averaged force profiles for each role of the interaction strategy are determined and implemented on a robot. Hence, not a desired object motion trajectory but a force profile representing a particular interaction role is executed in feedforward mode. This unidirectional signal exchange allows no reactions or adaptations to changes in the partner's behavior. Despite of this limitation, this points to the difference of controlling task execution or interaction with the partner as also discussed in section 3.1 about control objectives.

Classic force-feedback control of interaction

Feedback controllers compare the desired behavior to the current behavior and aim at minimizing the control error. If feedback control is applied in literature, the feedback is received either with respect to the desired task trajectory (discussed later) or about a desired interaction force with the environment (object or partner). Passive admittance/impedance controllers are common because they a) realize compliant behavior preventing excessive forces and b) are human-inspired. The latter is because the human arm is often modeled as impedance, and its parameters may be parametrized likewise.

Haptic robot followers [6, 84, 86, 192] are reactive-only as the interaction force with the environment is controlled. Implemented as compliant impedance controller [75], the robot needs no task knowledge but reacts on the forces applied by the human. By this, it assists by compensating the workload of the object. These first interactive approaches realized either constant impedance parameters or impedances with variable but pre-defined parameters [84]. This leader-follower approach is efficient in applications where the robot's task is to take over the load. In the cooperative handling of a single object, distributed mobile robots follow the human and show a caster-like behavior in Hirata and Kosuge [72], Hirata et al. [73].

Furthermore, many rehabilitation devices compensate the weight of a human body part, e.g., the leg [3, 205]. Similarly, the extender suggested by Kazerooni [97], Kazerooni and Guo [98] aims to increase human's mechanical strength by amplifying the human's applied force. The feedback controller of the robotic assistant aims at minimizing a force-based performance measure.

Advanced passive robotic followers adopt variable control parameters like the time-variant parameters of a virtual impedance/admittance [4, 32, 33, 83, 106, 191, 192]. The parameters of the interaction controller are adapted to the user's intention. As an instance, it is switched between two different stiffness values based on a velocity threshold in Ikeura and Inooka [83]. Similarly, in Duchaine and Gosselin [32, 33] the damping of the robot's impedance is adapted. In Tsumugiwa et al. [191, 192, 193], the impedance is adjusted on-line based on the sub-tasks, carrying or positioning, recognized by the robot. Though, still having no explicit task knowledge, these robots demonstrate one way to realize adaptive behavior in interaction control.

Controllers realizing one interaction control strategy

All of the approaches discussed so far focus on haptic interaction where only one of the involved parties shows pro-active behavior, i.e., interaction with passive partners (or passive environments). A first control approach with two active partners was already presented in section 2.3.2, but in the context of robot-robot interaction. Taking into account the feasibility and controllability of the interaction state, this control structure can be transferred, in general, to the interaction of human and robot partners.

In the context of haptic human-robot interaction, dyadic collaboration of two equal partners both contributing pro-actively to task execution is addressed by, for example, Corteville et al. [25], Lawitzky et al. [107], Oguz et al. [133], Suzuki et al. [181]. In Corteville et al. [25], the constant fraction of a desired task trajectory is tracked by a compliant feedback controller in a fast point-to-point motion. In Lawitzky et al. [107], the interaction controller is a combination of a feedback and a feedforward controller tracking the desired object trajectory. The robot's contribution is determined by a so-called effort sharing policy. In the experiments, different but constant effort-sharing parameters were applied. In contrast, the robot's role is dynamically changing in Oguz et al. [133], Suzuki et al. [181]. In Suzuki et al. [181], the level of assistance is adapted on-line and continuously based on the user's skill level. The parameters of an ARX model describing the user's skill level are identified continuously in a point-to-point task. Considering this, the degree of assistance is adjusted based on a model of a virtual expert. In Oguz et al. [133], it is switched between different levels of assistance based on task-execution performance. The switching triggered by force thresholds is realized by applying a finite state machine. Though introducing different roles and adapting the parameters to the human, these approaches focus on improving task performance and realize one control strategy.

Controllers realizing multiple interaction control strategies

Another way to approach the challenge that the interaction partners can take on different roles is presented by Evrard and Kheddar [40, 41], Wang et al. [207, 209], Yamato et al. [218]. There, multiple control approaches are realized on the technical partner. It is either switched between these control strategies or their outputs are merged. In the context of human-like roles, this idea of several action controllers is discussed by, e.g., Reed and Peshkin [148], Stefanov et al. [178], Ueha et al. [197, 198].

As an instance, the robot is enabled to show follower or leader behavior by realizing two different control strategies. In Wang et al. [207], Yamato et al. [218], the robot adopts either of the two interaction controllers and switches between them depending on the human partner's estimated intention. In Evrard and Kheddar [40], the weighted sum of a follower and a leader controller is output. By this fusion, different values in-between the two extreme roles can be taken on by the robot. This approach enables different types of interaction, namely collaboration and conflict. Similarly, in Jarrasse et al. [90], three different action control laws are suggested, and the robot's action is obtained as the weighted sum of the outputs. There, the goal is to minimize the interaction force with the human as well as task performance. In Tsumugiwa et al. [193], it is automatically

switched between two controllers supplying different interaction strategies in dependence of the present sub-task. Wojtara et al. [216] realized an interaction controller that lock/free different degrees of freedom. It has to be switched manually between them.

Motor unit

Like the sensory subsystem, the robot's motor unit comprises low-level processes, such as filtering, friction compensation or drivers for the actuators. The robot's actuators are usually controlled by low-level controllers consisting of feedback as well as feedforward components. Often they are realized as high-gain position, velocity or force controllers.

Robotic motor units, in particular their actuators, span a wide range, starting from classic DC motors to highly complex artificial (humanoid) muscles and hands. The type of motor unit characterized by its degrees of freedom, bandwidth or work space influences significantly its action and interaction capabilities. Different challenges are faced in their mechanical as well as controller design. The design of robotic motor units is not the focus of this dissertation. Thus, the interested reader is referred to, e.g., Butterfaß et al. [19], Craig [26], Minato et al. [124], Tondu and Lopez [190] for more details. If necessary, the effect of the applied robotic systems on the interaction behavior is discussed in the respective section.

Intention recognition

Before the robot's individual intention can be integrated with its partner's intention, the latter has to be recognized. As the partner's intention is a latent psychological concept, it is not directly measurable by the robot but has to be estimated based on prior knowledge and information obtained from environmental feedback.

In haptic collaboration, the partners' intentions are not restricted to the object's motion but also include the way each partner contributes to task execution and the way they interact with each other. Hence, the intention of the individual action plans towards the shared goal is composed of the following components:

- The task goal of the partners, e.g., to move a table to the other end of the room, is a high-level, abstract *goal intention* [176, 222]. The successful integration of both partners' goal intentions defines the shared goal.⁶
- Each partner has a *trajectory intention* about the desired trajectory or force profile to execute the task.
- The *interaction-strategy intention* describes each partner's desired interaction strategy at a given time.

⁶As it is assumed in the context of this thesis that the partners have already agreed on a shared goal, the goal intention is not considered in more detail.

- The *role intention* refers to the parametrization of the different interaction control strategies and to the partner's share of each of them.

Up to date, different approaches to recognize these intentions are presented in literature, reaching from inferring the user's intention simply based on force thresholds or changes in the force to complex HMMs. As an instance, the goal intention in Corteville et al. [25], Hölldampf et al. [77, 78], Maeda et al. [114] is estimated by evaluating the forces applied by the user. The role intention in Solis et al. [176] is determined by force thresholds. The role intention in Duchaine and Gosselin [32, 33] is identified based on changes in the force applied. A similar approach is adopted by Oguz et al. [133].

In Tsumugiwa et al. [191, 192, 193], the robot recognizes the different sub-tasks, carrying or positioning. These goal-oriented intentions are recognized based on either a) a passivity index and the forces applied by the human [191, 192] or b) the human's estimated arm stiffness [193]. In Suzuki et al. [181], the parameters of an ARX model describing the user's skill level are identified online.

In Solis et al. [176], Yu et al. [222], a HMM is utilized to recognize the user's goal intention and, in Wang et al. [206, 207], to estimate the human's role intention. In the latter case, this enables the classification of human behavior in "passive" or "active" in a human-robot handshake scenario. Based on this, a respective adaptation of the control parameters is realized.

In the next step, the partner's estimated intention has to be integrated with the robots own intention.

Intention integration

Intention integration is one of the key components of haptic collaboration. The objective of the intention integration subsystem is the continuous integration of the robot's current individual intention with the estimated partner's intention. Starting with the robot's initial intention derived from prior knowledge, the robot has to continuously negotiate on an individual intention that, then, determines the structure and parametrization of the control unit. As illustrated in Fig. 3.4 the process of intention integration begins with a compatibility check of the partners' individual intentions. Based on the result of this comparison, the robot negotiates a new individual intention by either adapting its previous intention to the partner's intention or by dominating it and keeping its intention.

This intention integration involves decision-making as well as adaptation processes. Decision-making generally refers to the act of choosing one available option out of several possibilities. Adaptation describes the adjustment to changing environmental conditions, meaning here mainly the perceived environmental feedback, in particular, the partner's behavior. Hence, adaptation can be understood as a continuously on-going process of decision-making based on new information. Intention integration is addressed in more detail in Groten et al. [234].

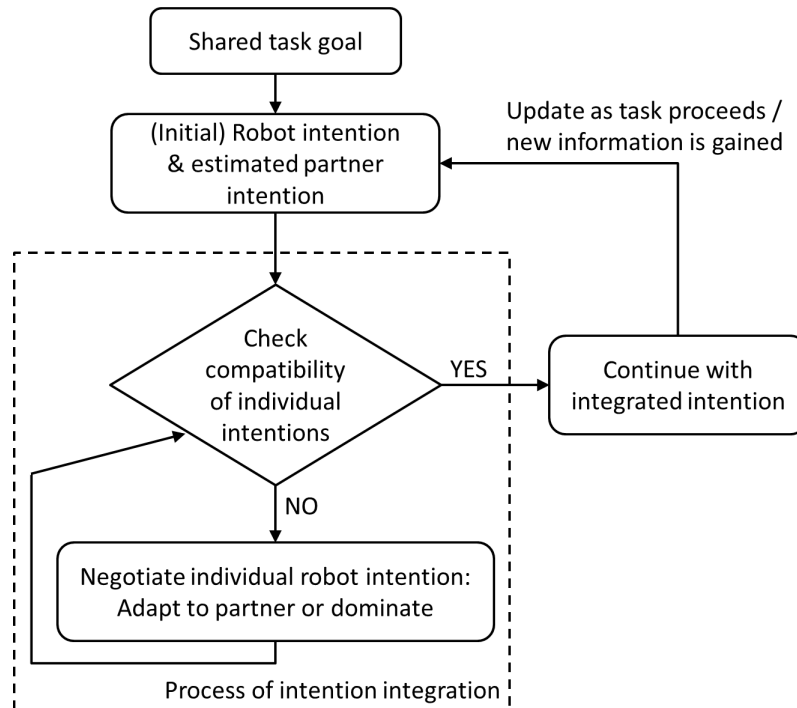


Fig. 3.4: The process of integrating own intentions with the estimated partner's intention to achieve successful collaboration behavior. Figure adapted from Groten et al. [234] ©2013 IEEE.

Please note that for successful haptic collaboration, the partners' intentions do not have to be the same, but they have to be compatible.

In haptic human-robot collaboration, it is assumed that the interacting partners have a shared goal that was successfully negotiated on. Still, intention integration has to take place with respect to the other types of intention that are introduced in the previous paragraph.

In literature, some haptic interaction robots adapt their behavior to the human's intention. This involves, e.g., deciding on a particular, pre-programmed task trajectory out of several that are available (stored in the knowledge base) [176, 222] or a parameter adaptation of the minimum-jerk trajectory executed by the robot [25, 114]. In Corteville et al. [25], the resulting trajectory is additionally adjusted to the user's need for assistance which relates to integration of role intention. Similarly, in Hölldampf et al. [77, 78] the step size of a robotic male dancer, i.e., its task trajectory is scaled based on the forces applied by the female human partner. In these examples, the robot's behavior is always adapted to the recognized human's intention. Hence, intention integration takes place only to a limited extent as the robot has an initial intention but adapts it to the human's intention as soon as it recognizes a deviation.

Knowledge base

The *knowledge base* contains the robot's stored information on tasks, environments, the partner's behavior and interaction strategies. It is often suggested to store the knowledge in form of internal models, cf. section 3.2.1. The idea of internal models is widely accepted in literature [27, 214, 217]. It is grounded in the formation of models of the real-world inside a human to allow for the prediction of the system's state and future events. This concept applied to robot controllers in haptic human-robot collaboration comprises

- its extension from models established inside of humans to models stored within a general interaction partner, whether human or robot;
- that in the ideal case, each interaction partner has an internal model describing all relevant aspects of the collaborative task;
- that each interaction partner plans its control actions in relation to the stored models.

To enable the application of the knowledge in the intention negotiation as well as control level of the control framework, the internal models need to have an appropriate system-theoretic form to be compatible with them.

Further, the knowledge base is not static but always modified and extended based on information obtained from its surroundings, i.e., the robot is learning. Hence, there is a bidirectional information exchange with all the other sub-modules involved. The learning comprises the optimization of existing models as well as the identification of completely new ones. Different learning methods may be utilized. The interested reader is referred to Argall et al. [7], Matarić [117] for an introduction to the broad field of robot learning. In haptic human-robot collaboration, only little attention has been paid to learning so far, except for, e.g., Calinon et al. [20], Medina Hernandez et al. [122].

3.2.4 Discussion

The introduced control framework is derived in the context of joint object-manipulation tasks. As it satisfies all the requirements identified in Groten [65], it is not restricted to this type of task but applicable to a wide range of scenarios in haptic human-robot collaboration. This generality is demonstrated by the integration of the state-of-the-art literature with the framework. Thereby, existing models for each of the control framework's subsystems are introduced and discussed. This reveals that trajectory planners, controllers or models that are applied in dyadic human-robot collaboration are commonly not adapted to this scenario but transferred from haptic interaction with passive environments without modifications. However, Desmurget et al. [29], Gentry et al. [54], Reed et al. [147] showed for different parts of the framework that this is feasible only to a very limited extent. New approaches have to be found.

One of the main characteristics of haptic collaboration is that task execution and interaction with the partner cannot be causally separated. Thus, they have to be considered simultaneously in all subsystems of a control architecture. However, existing approaches of robot control in joint object-manipulation tasks focus mostly on either assistance in task execution or the interaction with the partner. The presented control framework closes this gap and, thus, enables the design of new controller structures.

3.3 Conclusion

In summary, this chapter identifies control objectives and presents a new generic control framework in the context of haptic human-robot collaboration. The **control objectives of collaborative, human-robot object manipulation** relate mainly to **task performance, cooperation** and **coordination** (commonly evaluated by effort and workload sharing) or **haptic communication** for information exchange. In this clearness, these different types of control objectives were identified and discussed for the first time. “Intuitive” or “human-like” interaction behavior is not defined as an independent control objective but a manifestation of a control objective, e.g., human-like task performance or human-like cooperation. To achieve intuitive interaction behavior of a technical partner, the appropriate definition of the control objectives is a key component.

Taking human-like interaction behavior as one instance of intuitive interaction behavior, the definition of interaction controllers requires the understanding, i.e., the analysis and modeling, of human, dyadic interaction behavior that can be implemented on a robotic system. As there is only little knowledge about how a human dyad interacts in a collaborative, haptic task, this is approached in the remainder of this dissertation.

Control objectives have a direct effect on the control structure. The huge variety of different control structures presented in literature demonstrates that this research field is at a point where it has to move from one-problem solutions to a **generic control architecture**. Such a control architecture that is applicable not only to one specific task but a **wide range of scenarios in human-robot collaboration** is introduced in this chapter. Within the control framework, the involved subsystems are defined and put in relation to each other. It is pointed out that task execution and interaction with the partner are considered simultaneously in all subsystems. In order to enable a straightforward design, implementation and analysis on a real robotic system, a strict separation between a control level and higher-level information-processing levels is made. By defining one main, distinct closed control loop, the behavior of the robot can be designed and analyzed by established control methods. This further allows for a modular controller design which is required because of the high complexity of collaborative control behavior.

Additionally, existing models can be classified, integrated and combined with each other by applying the presented, novel top-down control framework for a robot, haptic collaboration

partner. **State-of-the-art models are integrated with the control framework** by presenting and discussing them for each of the involved framework components.

One of the framework's subsystems, the interaction controller, is addressed in more detail in the remainder of this dissertation. In the following chapter, a performance model that describes dynamic, human, haptic interaction behavior is established. The model is embedded into the framework to guarantee its integration with existing work as well as its systematic evaluation and implementation on a robotic system.

Even a step further is taken by a new structure of an interaction controller that is presented in the outlook of this dissertation, cf. section 6.2.2. Like the whole control framework, this generic structure of an interaction controller allows a modular design of new approaches and the integration and combination of existing ones. Furthermore, it gives **concepts related to human behavior, like roles or interaction strategies, an explicit meaning in the context of controllers**. This simplifies interdisciplinary research by providing a common basis.

4 Haptic, human, dyadic interaction in a compensatory tracking task

Human-inspired, haptic interaction behavior of robots is addressed by, e.g., Evrard and Kheddar [40, 41], Jarrasse et al. [90], Lawitzky et al. [107], Oguz et al. [133], Suzuki et al. [181], Tsumugiwa et al. [193], Wang et al. [207], Wojtara et al. [216], Yamato et al. [218]. Though their goal is to develop human-like, interactive robot behavior, human behavior as a baseline condition and benchmark for robot behavior is hardly utilized. This is due to a lack of a deeper understanding of haptic, human collaboration behavior. However, it is a key requirement for the systematic derivation of control objectives and control structures leading to human-like behavior.

To close this gap, human, dyadic, haptic interaction behavior has to be experimentally analyzed and modeled to enable

- a deeper understanding of the underlying processes of haptic, human collaboration and
- an integration into robot control strategies to provide intuitive human-robot interaction.

Thus, the goal of this chapter is two-fold. It mainly aims at the identification of a **dynamic, task-specific control model of human, haptic interaction behavior**. This forms the basis for the design of an interaction controller of a technical partner. Additionally, it strives for **an analysis that leads to deeper insights into haptic, dyadic interaction**.

In general, it is distinguished between controlling the object's motion and the rather interaction-related variables workload sharing and internal forces. In the present chapter, the focus is on the object's motion, i.e., the result of the partners' interaction. A task-specific, dynamic, human performance model that is well-established to describe an individual's behavior in tracking tasks is successfully transferred to dyadic task execution. This transfer of a model describing an individual operator's dynamic behavior to the behavior of an interacting dyad executing the task in haptic collaboration is approached in this dissertation for the first time. Model identification and validation is conducted based on experimental data of a 1-dof compensatory tracking task.

By relating the resulting forces as well as the external forces of the partners to the task error, this novel model describes human interaction control behavior. Thus, with reference to the previously-introduced control objectives, it is aimed at human-like error-correction

behavior. By this, if transferred to a robot, intuitive haptic interaction behavior can be achieved.

The model and experiment are embedded into the framework presented in chapter 3 as well as an experimental paradigm. By this, a straightforward transfer of the human interaction control model to a technical partner, i.e., the interaction controller subsystem of the control framework is ensured.

Furthermore, an analysis of the experimental data is conducted: In haptic human-robot collaboration tasks, a technical partner is typically introduced to support the human in task execution and to increase performance. For this reason, the improvement of task performance is a key factor in the design and evaluation of robotic partners, and its evaluation an integral part of the analysis of human, haptic collaboration behavior. Thus, task performance in the presented experiment is evaluated. Furthermore, the dynamic, human performance model of an individual within an dyad assumes that internal forces are built up between the partners. Thus, the experimental analysis presents a characterization of the internal forces. Additionally, requirements and guidelines for future controller design are derived. Finally, internal forces are related to task performance in a preliminary analysis. These results point towards a deeper understanding of the underlying processes of haptic, human interaction behavior.

To derive open challenges and research questions in more detail, the state of the art of haptic interaction studies as well as of modeling approaches is presented in the following.

Please note that the initial approach and results of this chapter have been published before in Feth et al. [224] ©2009 IEEE and Feth et al. [225] ©2009 IEEE. With permission, they are reprinted in large parts in the following¹. [224] is mainly reused in sections 4.1 to 4.4.3, section 4.5 and appendix A. Parts of [225] are mainly reprinted in section 4.4.4 and appendix A. Beyond that, the present chapter significantly differs from those publications, because

- modeling approach and experimental identification results for each individual within the dyad are presented for the first time;
- analysis and modeling results are based on a larger experimental-data set;
- the discussion of section 4.4.4 is backed up with a new analysis of the experimental data.

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4.1 State of the art

The state of the art of experimental studies analyzing haptic, human interaction behavior as well as modeling approaches to describe this behavior are presented to identify open research challenges.

4.1.1 Experimental studies

Experimental studies approaching haptic human-human interaction aim at different research questions. Some studies aim to describe and understand the effect that interaction with a partner, contrasted to a single person's behavior, has on performance. Others address the effect of haptic feedback on performance, compared to visual-only feedback. Few studies approach interaction strategies and role allocation in haptic, human collaboration. Finally, in case of technically-mediated, human interaction, some studies focus on the effect that different characteristics of the technical systems mediating the haptic interaction have on performance.

Influence of system characteristics on interaction behavior: Studies focusing on the understanding of effects and behavior changes in haptic human-human interaction caused by different technical systems consider parameters like

- network delays [5, 58, 67, 118, 158],
- control parameters [104] or
- weighting functions influencing the feedback between the partners and the effect they have on the object [38, 100, 131, 183].

Throughout this dissertation, the same experimental hardware, presented in section 4.4.1, is used. Hence, the effect of different parameters or characteristics of technical systems is not further discussed.

Effect of adding a partner on task performance: To show the positive effect the introduction of a haptic collaboration partner has in a certain scenario, studies are conducted that compare conditions where an individual participant executes the task to conditions where a dyad performs the task. Behavior changes in partner trials compared to individual trials are analyzed based on task-performance measures. Research has focused mainly on tasks that can be accomplished by an individual but where the introduction of a partner is expected to simplify task execution. It was shown by Gentry et al. [53, 54], Glynn and Henning [57], Reed et al. [147], Ueha et al. [197, 198] that performance is increased if there is haptic interaction with a partner compared to task execution by an individual in 1-dof pointing movements, 1-dof cyclical movements and 2-dof tracking tasks, respectively. Experiments were conducted with real or virtual objects.

Effect of adding the haptic modality to human-human interaction tasks on task performance: Unlike haptic human-human interaction via a real object, virtual-environment studies [9, 58, 155, 157] allow the comparison of visual-only to visual-haptic conditions and, hence, allow to approach the effect of adding the haptic modality to an interaction task. When boxes had to be stacked collaboratively in a VE, Sallnäs [155], Sallnäs et al. [157] found that haptic force feedback significantly increases task performance in terms of failure rates. Similar results are reported by Basdogan et al. [9] for a ring-on-wire task. In Groten et al. [232], it was shown that the effect of haptic feedback on task performance becomes the more relevant the higher the required negotiation effort between the partners is in the considered pursuit tracking task.

Analysis of dyadic interaction strategies and roles: There are few approaches that define and identify human, dyadic, haptic interaction strategies. Natural energy exchange was addressed in Feth et al. [225]. It is shown that there is an asymmetric energy flow between the partners via a virtual object. The cause of energy flow between the virtual object and the human is either the interacting partners pushing/pulling against each other or one partner generating kinetic energy while the other partner is dissipating kinetic energy - thus, accelerating and decelerating the object. This is related to the work of Stefanov et al. [178] where the non-exclusive roles of executor and conductor are introduced based on internal forces, velocity and acceleration of the object.

In Rahman et al. [145], an object-carrying task in 1 dof is considered and a leader-follower strategy is identified in the following way: The motion of the object is described by Newton's law $m_o\ddot{x} = f_1 + f_2$ with m_o and \ddot{x} the mass and acceleration of the object, respectively. f_i ($i \in \{1, 2\}$) is the force applied by the partners. Further, $f_1 = \alpha_1 m_o \ddot{x} + f_i$ and $f_2 = (1 - \alpha_1) m_o \ddot{x} - f_i$ where α_1 is called a "distribution ratio of the inertia load" [145], and f_i is the internal force. According to them, "the nature of the internal forces is unknown" [145]. Because of this, α is deduced indirectly by the correlation coefficient ρ . ρ is obtained by correlating the force applied by the participants with the resulting acceleration of the object. It is argued that the correlation coefficient is the higher the higher the contribution of the respective participant is to the motion of the object. By applying this method, it was found that, on average, participants take on different follower-leader roles if interacting with different partners. A participant was considered a leader if the correlation coefficient ρ was larger 0.5 and a follower, else.

A similar construct is introduced by Reed et al. [149] referring to the *dominance* ratio of the interacting partners for a 1-dof rotational task. There, $\alpha_1 = f_1/(f_1 + f_2)$ and $\alpha_2 = f_2/(f_1 + f_2)$. This definition is complementary for their special case that the sign of the forces f_1 and f_2 is the same. Based on this dominance ratio specialized and non-specialized couples are identified in a 1-dof rotational pointing task in Reed and Peshkin [148]. For the specialized case, two different interaction strategies are suggested: accelerator/decelerator and left/right. If an accelerator/decelerator interaction strategy is established, one partner contributes mainly to the acceleration of the object and, at the same time, the other partner to the deceleration of the object. In case a left/right-strategy is established, one partner would predominantly contribute to forces of the object to the left and the other

partner to the right, i.e., $f_1 > 0$ if $\dot{x}_o > 0$ and $f_1 < 0$ if $\dot{x}_o < 0$. In the non-specialized case, both partners contribute to each phase equally. They found that partners adopt an accelerator/decelerator-strategy more often than a left-/right interaction strategy or a non-specialized behavior in the task.

Similar results were found by Reinkensmeyer et al. [151] in a 1-dof rotational task not for dyadic interaction but for bimanual task execution using a simple two-hand grasp where the partners cannot pull away from each other but only push against each other. The experimental results reveal that also one hand accelerates and the other one decelerates the object. Additionally, large grasping forces were built up by the participants.

In both studies, the role allocation to the partners does not remain constant over the trials but may switch from trial to trial. It is discussed that these interaction strategies are related to the internal forces (in case of Reed and Peshkin [148] it is referred to as “*difference force*”) which are built up between the partners. Melendez-Calderon et al. [123] recently presented EMG results of a 1-dof wrist flexion/extension task supporting this result. They identified interaction strategies “*on which an agent damps the movement by pure co-contraction or on which both agents simultaneously pull or push away or against each other*” [123].

4.1.2 Models of haptic, human collaboration behavior

Modeling approaches to describe human behavior in haptic object-manipulation tasks are revised briefly in the following. Most human behavior models aim at describing the interaction behavior of humans with technical systems, objects and environments [45, 46, 188] but not with a (human) partner. Please refer to section 3.2.3 for more details. If models originally established for individual operators are applied to describe the interacting partners’ actions, the model fit usually decreases significantly [54, 147, 224]. In particular, in Feth et al. [224], it was shown that the individual’s behavior within a dyad cannot be described by the individual’s model in a compensatory tracking task. This illustrates the necessity of identifying models particularly adapted to human, haptic collaboration behavior.

As introduced in the previous paragraph, in Reed and Peshkin [148], Reed et al. [149], the interaction strategy of “*accelerator/decelerator*” was identified for human, dyadic interaction behavior in a 1-dof rotational task. The decelerator role was implemented as a feedforward model on a robot which was derived from characteristic force trajectories. In Ueha et al. [197, 198], they found that in a 1-dof crank-rotation task one partner applies forces in radial and the other one in tangential direction. However, the statistical power of their results is very limited as they found these strategies only in one dyad out of eight. Still, a robot is realized that adapts the “*radial*” role and applies radial forces only “*in the direction which go out of the center of rotation*” [198]. In Wang et al. [209], it was identified that humans adopt a rather active or passive behavior in a handshake scenario. Based on this result, control strategies for an interactive robot were derived.

Except for these approaches, no dynamic model describing human, dynamic behavior in a dyadic, haptic task could be found in the current literature.

4.2 Open challenges

In summary, the state-of-the-art section shows that there is a profound field of haptic interaction studies. More or less all of the studies reveal a positive effect on task performance by adding a partner and the haptic modality to manipulation tasks. This motivates the introduction of a technical partner to such tasks. However, only a limited number of approaches is concerned with models of haptic, human collaboration behavior that could be implemented on a robotic partner to achieve intuitive, *human-like*, haptic interaction behavior.

4.3 Approach

To address these research challenges and to gain a deeper understanding of haptic, human collaboration behavior, the following approach is applied in the remainder of this chapter:

- A systematic experimental approach is presented to draw meaningful conclusions and to allow for a generalization of the results.
- A human performance model that is well-established for single operators [119] is introduced, discussed and transferred to dyadic interaction.
- The experimental data is analyzed with respect to task performance and internal forces.

4.3.1 Experimental paradigm

The goal of this chapter is to model human interaction control behavior dynamically. Based on this, requirements to be met by an interaction controller enabling human-like robot behavior in a joint object-manipulation task are to be gained. Thus, the focus of this chapter is on the actual control loop of the control framework presented in chapter 3, as illustrated by Fig. 4.1. Intention negotiation and knowledge base are of minor importance in the following.

To enable a straightforward transfer of the human model to an interaction control strategy of a technical partner, the main control loop, in particular the interaction controller, has to be “cut free” experiment-wise. The input to the interaction controller, i.e., the shared goal as well as the participants’ intended object trajectory has to be measured externally. However, the shared goal as well as the intended trajectory is generally a cognitive, hidden

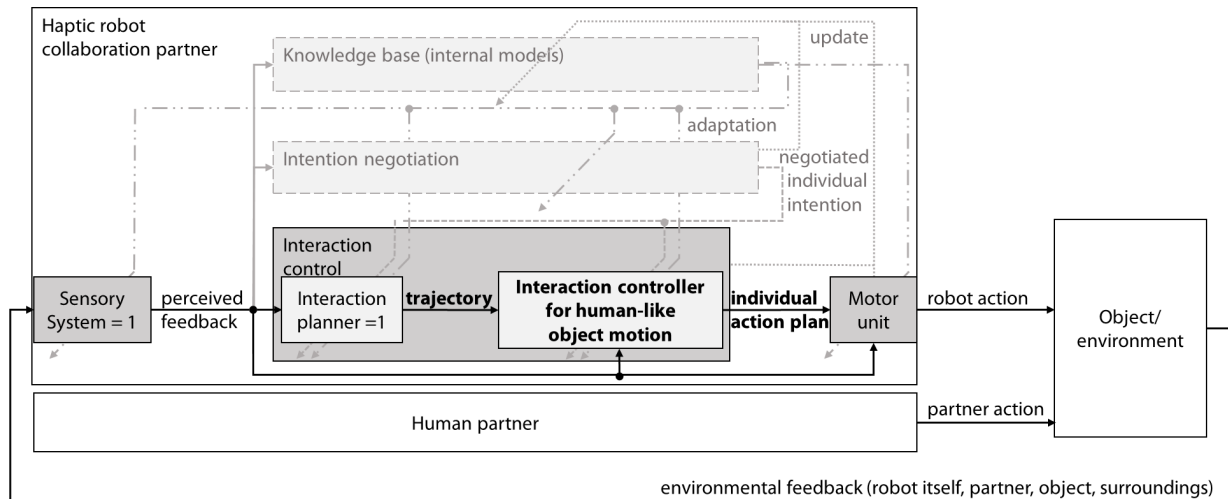


Fig. 4.1: Adapted version of the control framework presented in chapter 3: The focus is on the actual control loop. Thus, intention negotiation and knowledge base are greyed out. The shared goal, i.e., a reference trajectory for the object’s motion, is introduced externally by the experimental design such that it is the same for both partners.

representations in haptic collaboration tasks – thus, not directly measurable. To approach this challenge, the experimental paradigm presented by Groten [65] is applied.

In Groten [65], an experimental paradigm² for haptic collaboration research of joint object-manipulation tasks is introduced. It is adopted here and briefly summarized highlighting its strength (in parts from Groten [65]):

- A jointly executed tracking task is chosen as a structured experiment representing real scenarios of haptic collaboration for several reason. For example, joint action plans are not only cognitive representations but are made explicit in the experimental design in form of a desired reference path.³ In addition, tracking tasks are a well-studied field for individual performers as discussed in the next section.
- Two levels of haptic collaboration are defined: The first level refers to a tracking task where both partners have only one and, hence, the same path to follow. On the second level, binary decision making is introduced. At particular sections, the path separates, and the partners have to decide which way to follow. Their preferences are controlled externally by, e.g., displaying different information about the path to them.
- The tracking scenario and the paradigm allow to move gradually and systematically from highly-controlled experimental settings to real-world applications. Thus, the generalizability of results obtained in a scenario of low complexity can be transferred and validated in more complex scenarios.

²A side note: The experimental paradigm presented in this section demonstrates best the highly interdisciplinary approach required in this field of research as it shows how modeling approach and experimental design need to go hand-in-hand.

³This is further strengthened by Rasmussen [146]. There it is stated that tracking tasks are one of the few examples where *only* skill-based behavior (the lowest level) is utilized by the human.

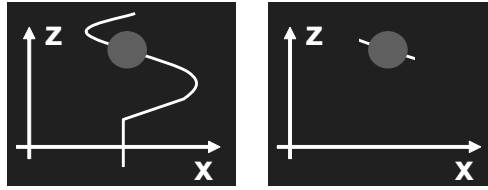


Fig. 4.2: Pursuit (left) and compensatory (right) tracking task: In a pursuit tracking task, a preview of the path is displayed. In a compensatory tracking task, only the current position of the track is visible.

- Control conditions, e.g., “individual person”, “no haptic feedback”, are defined and assessed with respect to the particular application, to approach different research questions and to confirm the results of the respective state of the art.

In general, interacting partners have to plan and negotiate on the object trajectory in joint object-manipulation tasks. However, to allow an identification of the interaction controller, the output of the interaction planner, i.e., the partners’ intended behavior has to be controlled externally. This is facilitated by a jointly executed tracking task defined by a reference trajectory that is graphically visualized and the same for both interaction partners. In this task, both partners are instructed to move the joint object along the same path⁴. As a result, differences between the dyad’s desired and actual object motion as well as the respective forces are made observable and, thus, can be analyzed. This leads to a simplification of the control framework in the context of this experiment, cf. Fig. 4.1.

In more detail, the tracking task is realized in a virtual-environment setup enabling haptic interaction between the partners by haptic interfaces, appropriate haptic rendering algorithms and a virtual, visual representation of the desired object trajectory. This approach is preferred to a robot-mediated task taking place in reality [148, 207] because it offers the advantage of controlled manipulation of the visual trajectory information. Additionally, an individual user as well as a visual-only control condition can easily be introduced. Similar tracking tasks have been analyzed by Basdogan et al. [9], Glynn and Henning [57], Glynn et al. [58].

The visual information about the intended trajectory is displayed on separate screens for each partner and can be manifested in different ways, e.g., different prediction horizons can be realized influencing the participants’ possibilities to plan their actions in advance what might lead to different action plans. In particular, compensatory and pursuit tracking task are discriminated, compare Fig. 4.2. To allow the identification of a classic feedback interaction without predictive components, a compensatory tracking task is analyzed in the following.

⁴Except for differences in their perceptual systems which are assumed to be negligible here.

4.3.2 McRuer's crossover model in dyadic, haptic collaboration

Different approaches describing human control behavior are found in human performance modeling. They are applied to describe a pilot's, i.e., individual's behavior in pursuit and compensatory tracking tasks. A variety of models describing the user's dynamic control behavior were established. The operator's behavior is modeled mainly as a combination of feedforward and feedback control structures to control task execution. Thereby, highly-trained operators behave mainly like a feedforward controller. In contrast, untrained persons with no task knowledge are described by feedback architectures. A good survey on this topic is provided by Jagacinski and Flach [89], Young and Stark [221]. The main statements are briefly summarized:

- **A quasi-linear feedback model** describing the operator's dynamic behavior is identified by Elkind [37], McRuer and Jex [119] for compensatory tracking tasks with different plant dynamics in a virtual environment. It is shown by McRuer and Jex [119] that the operators adapt their behavior to the dynamics of the task which is characterized by the object's impedance. Based on this result, quasi-linear feedback models describing the operator's dynamic behavior for compensatory tracking tasks in interaction with different plant (=object) dynamics are established. This idea is extended by Reid [150] to pursuit tracking tasks, again applying feedback control laws.
- More complex, **non-linear models describing the operator as a combination of feedforward and feedback control** were introduced in Davidson et al. [28], Hess [69].
- **Optimal (state-space) control** is also a way to model human behavior in pursuit and compensatory tracking tasks [102]. It is *“based on the assumption that the human can be mimicked by a controller which estimates the state of the controlled system and develops a control strategy which minimizes a performance index [185].* This was realized in Kleinman et al. [102] by applying a Kalman-Bucy Filter for the state estimation by solving a Linear-Quadratic-Regulator problem minimizing a performance index. However, beside this performance index, only little is known about optimization criteria relevant for haptic, human interaction.

Except for simulations in Penin et al. [142] and the author's own work [227, 229], none of these models established for tracking tasks has been applied in the context of haptic human-robot collaboration. How to transfer models describing an individual operator's dynamic behavior to model the behavior of an interacting dyad executing the task in haptic collaboration is approached in this dissertation for the first time.

The focus is on one of the above-introduced approaches: The model of Elkind [37], McRuer and Jex [119] is chosen to be transferred to dyadic interaction. This approach is picked because its implementation as part of the interaction controller is straightforward due to its feedback structure. Furthermore, it is assumed that the human operators are untrained, and, because of this, feedback characteristics dominate in their behavior.

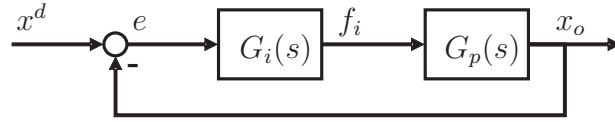


Fig. 4.3: Human, individual behavior modeled as feedback control in a compensatory tracking task, ©2009 IEEE: Block diagram of an individual operator $G_i(s)$ moving an object $G_o(s)$ along a given reference trajectory x^d ; the tracking error $e = x^d - x_o$ is compensated by applying the force f_i

In the following, the various forms of this crossover model approach are derived for the different experimental conditions (individual, partner) and involved parties (each partner, dyad).

The crossover model

In a compensatory tracking task the goal is to move an object along a given desired trajectory as exactly as possible. This crossover model [119] assumes a linear feedback structure for the human control behavior as shown in Fig. 4.3. It receives the tracking error

$$e = x^d - x_o \quad (4.1)$$

as model input where x^d is the given reference trajectory and x_o is the position of the object. The force f_i applied by the user to correct the error is the model output. It is assumed that the human reacts only on the current position error. The human's goal is the minimization of the tracking error.

The main idea of McRuer's approach is that *the human operator adapts her/his behavior to the plant characteristics* and behaves like a "good servo" in the region of the crossover frequency ω_c . This results in a *constant overall (open-loop) transfer function*

$$G_0(s \approx j\omega_c) = G_i(s) \cdot G_p(s) = \frac{K_c e^{-\tau_c s}}{s}. \quad (4.2)$$

where $G_i(s)$ is the transfer function modeling the human behavior (an individual performing the task) as a linear feedback controller. And, $G_p(s)$ is the plant transfer function which is (supposed to be) known. $G_i(s)$ is generally assumed to have the form

$$G_i(s) = \frac{F_i(s)}{E(s)} = \underbrace{\left[\frac{K(1 + T_z s)}{1 + T_n s} \right]}_{\text{control}} \cdot \underbrace{\left[\frac{e^{-\tau s}}{(1 + 2DT_\omega s + T_\omega^2 s^2)(1 + T_{N_1} s)} \right]}_{\text{perception-action loop}}. \quad (4.3)$$

The term in the first bracket describes the operator's planned control action, and the second term takes account for the human action-perception loop. Hence, K , T_z and T_n are the parameters of a classic causal (real) PD controller describing the intended human control actions to minimize the task error. τ is the time delay introduced by the perception-action loop. D , T_ω and T_{N_1} are characteristics of the human neuromuscular system. D

is the damping and $1/T_\omega$ is the corner frequency describing its low-frequency dynamics. T_{N_1} describes the system's high-frequency effects which commonly do not dominate in compensatory tracking tasks and, thus, are neglected in the following just as in McRuer and Jex [119]. This leads to

$$G_i(s) = \frac{F_i(s)}{E(s)} = \underbrace{\left[\frac{K(1 + T_z s)}{1 + T_n s} \right]}_{\text{control}} \cdot \underbrace{\left[\frac{e^{-\tau s}}{(1 + 2DT_\omega s + T_\omega^2 s^2)} \right]}_{\text{perception-action loop}}. \quad (4.4)$$

It is further assumed that the characteristics of the perception-action loop (second bracket) are independent of the intended control (first bracket). Thus, the dynamics of the perception-action loop are not be compensated by the control action.

According to McRuer et al. [120], the operator's behavior is characterized by a sufficient average tension of the arm in compensatory tracking tasks required for “*precision movements in tracking*” [120]. This assumptions leads to an over-damped system which, in combination with a low-frequency approximation of the second bracket, results in one real pole T_p . Then, the operator's behavior is described by

$$G_i(s) = \frac{F_i(s)}{E(s)} = \underbrace{\left[\frac{K(1 + T_z s)}{1 + T_n s} \right]}_{\text{control}} \cdot \underbrace{\left[\frac{e^{-\tau s}}{(1 + T_p s)} \right]}_{\text{perception-action loop}}. \quad (4.5)$$

This low-frequency, high-tension approximation⁵ is the form of the crossover model usually sufficient to describe the operator's behavior in compensatory tracking tasks and applied in the following unless stated otherwise.

It was shown in McRuer and Jex [119] that for different plants to be controlled, the operator shows different dynamic behavior because of the human adaptation capabilities. Thus, specific parts dominate in the first bracket of equation (4.5). In the present experiment, the plant to be controlled is a virtual object with inertia m_o . Thus, the plant dynamics of manipulating a rigid object with mass m_o (in free space) is given by

$$G_p(s) = G_o(s) = \frac{1}{m_o s^2}. \quad (4.6)$$

According to McRuer and Jex [119], this leads to a human control model with a PD-type control behavior of

$$G_i(s) = \frac{F_i(s)}{E(s)} = [K(1 + T_z s)] \left[\frac{e^{-\tau s}}{(1 + T_p s)} \right]. \quad (4.7)$$

$G_0(s)$ in the crossover region (as defined by equation (4.2)) is obtained by a low-frequency approximation assuming $T_z \omega_c \gg 1$. In order to ensure stability, $T_z > \tau_c$ is a necessary condition, with $\tau_c = \tau + T_p$. For more details please refer to the original work [119].

⁵For details of the derivation of this approximation please refer to the original work [120].

This approach found broad attention in literature. As an instance, it was extended by Reid [150] to pursuit tracking tasks (with a preview of the reference trajectory), again applying feedback control laws. Furthermore, it served as basis for more complex, non-linear models describing the operator as a combination of feedforward and feedback control [28, 69].

Individual model

For an individual performing a compensatory tracking task, the model as introduced by McRuer and Jex [119], McRuer et al. [120] is adopted one-to-one in this dissertation:

$$G_i(s) = \frac{F_i(s)}{E(s)} = [K(1 + T_z s)] \left[\frac{e^{-\tau s}}{(1 + T_p s)} \right] \quad (4.8)$$

where F_i is the force applied by the operator given a tracking error E in Laplace domain. The index i indicates individual behavior in the following.

Dyadic model

The transfer function of the interacting dyad G_d is considered next. It describes the relation of the resulting force applied by both partners to the task error. The respective block diagram is introduced in Fig. 4.4. The two human partners grasp the object represented by a point mass rigidly. Thus, their individual transfer functions G_1 and G_2 are connected in parallel, and the outputs, i.e., their applied forces, are summed. This leads to the resulting force

$$f_o = f_d = f_1 + f_2. \quad (4.9)$$

One main research question in the focus of the experiment is if an interacting dyad adapts its behavior to the plant and to each other in such a way that the resulting behavior is consistent with the idea of a constant overall open-loop transfer function. In the dyadic condition, this is

$$G_0(s) = (G_1(s) + G_2(s))G_o(s) \quad (4.10)$$

$$= G_d(s)G_o(s) \quad (4.11)$$

with the dyadic control behavior $G_d(s)$ according to the crossover model. If the crossover approach still applies, the resulting behavior of the dyad could be described as in the individual condition by

$$G_d(s) = \frac{F_d(s)}{E(s)} = \frac{F_o(s)}{E(s)} = [K(1 + T_z s)] \left[\frac{e^{-\tau s}}{(1 + T_p s)} \right]. \quad (4.12)$$

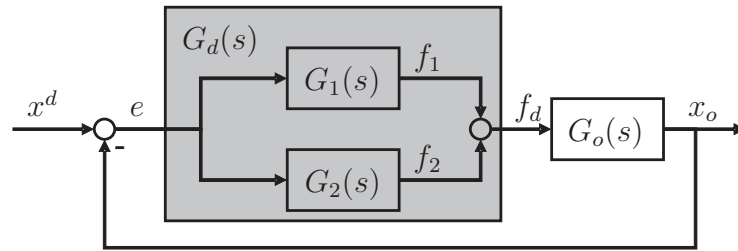


Fig. 4.4: Human, dyadic behavior modeled as feedback control in a compensatory tracking task, ©2009 IEEE: Block diagram of two partners moving a joint object collaboratively along a given reference trajectory; f_1 : force applied by partner 1, f_2 : force applied by partner 2, f_d : resulting force applied on the object, x^d : reference trajectory, x_o : position of the object, e : tracking error, $G_1(s)$: transfer function of partner 1, $G_2(s)$: transfer function of partner 2, $G_d(s)$: dyadic transfer function

Model of each individual within a dyad

The identification of the dyadic model is important for an understanding of haptic, human interaction. But, for an implementation on a robotic system, a control model of each individual partner within the dyad is required, i.e., $G_1(s)$ and $G_2(s)$, have to be identified.

In the context of haptic interaction, the approach of McRuer and Jex [119] has the capability of describing the partners' external forces, for the following reason: Only the external forces cause the object motion. Internal forces describe if the partners push against or pull away from each other and have no direct effect on object motion. The crossover model has the tracking error as input and the force to correct the error as output. It aims at the minimization of the tracking error, hence on the object motion. Thus, the transfer functions $G_1^e(s)$ and $G_2^e(s)$ describing the partner's external forces as a function of the tracking error can be modeled as depicted in Fig. 4.5.

A comparison of this controller structure of the interaction controller module with the control structure in section 2.3.2 reveals their close relation – although they come from different research fields: External and internal forces are controlled independently in both approaches.

In Feth et al. [224], it is shown that the individual's behavior within a dyad cannot be described by equation (4.5). Assuming that the general idea and the respective models of McRuer and Jex [119], McRuer et al. [120] still hold for an individual within a collaborating dyad, this result can be caused by either a change in the control behavior (first bracket in equation (4.5); determined by the plant characteristics) or a change of the characteristics of the perception-action loop, in particular the neuromuscular system (second bracket in equation (4.5)). In the following, the effect of dyadic, haptic interaction on equation (4.5) are examined carefully to derive the appropriate transfer functions $G_1^e(s)$ and $G_2^e(s)$.

First, the second bracket of equation (4.5) is addressed in more detail. Though the human reaction time varies to some extent, it is usually more or less constant within a human. Thus, it is assumed that this remains unchanged in the partner condition.

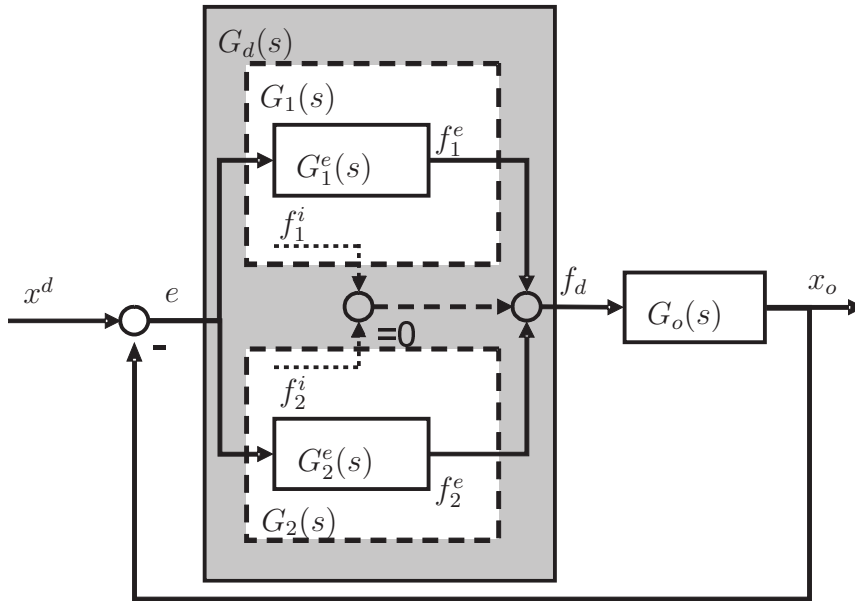


Fig. 4.5: Human, dyadic behavior modeled as feedback control in a compensatory tracking task, ©2009 IEEE: Block diagram of two partners moving a joint object collaboratively along a given reference trajectory; It is distinguished between the control of the internal and external forces; f_1 : force applied by partner 1, f_2 : force applied by partner 2, f_d : resulting force applied on the object, f_1^e, f_2^e : external forces of the two partners, output of the respective transfer functions $G_1^e(s)$ and $G_2^e(s)$, f_1^i, f_2^i : internal forces of the two partners, x^d : reference trajectory, x_o : position of the object, e : tracking error, $G_1(s)$: transfer function of partner 1, $G_2(s)$: transfer function of partner 2, $G_d(s)$: dyadic transfer function

However, haptic interaction has a significant effect on the low-frequency, *high-tension* assumptions made about the human neuromuscular system: In this context, the results presented by Melendez-Calderon et al. [123] are of great importance. Based on EMG data, they identified redundant strategies how an interacting dyad achieves good task performance in a tracking task: either by increasing the co-contraction of each partner's arm and, hence, its damping or by simultaneously pushing against or pulling away from each other. In the first case, the tension within each partner is increased whereas, in the latter case, the tension within/between the partners is increased. This last aspect relates directly to internal forces built up between the interacting partners. Thus, if the partners prefer to build up internal forces instead of muscle tension, a revision of the low-frequency, high-tension assumption of the human neuromuscular system to be described by one real pole is necessary.

To be more precise, tension within a partner and between the partners (muscle tension and internal forces, respectively) can, of course, co-exist. In the present context, the goal is not to rule out one of these types of tension or to give an in-depth explanation for either of them, but, to address which of them dominates with respect to modeling assumptions (compare, also, section 4.4.4).

As already mentioned, it was shown in Feth et al. [224] that the high-tension approximation of the crossover model is not appropriate to describe the control behavior of an individual within an dyad. Furthermore, in Groten et al. [231], it is revealed that relatively high internal forces are built up between the interacting partners in a similar tracking task. Similarly, Reed and Peshkin [148] reported high internal forces in a rotational pointing task and in Reinkensmeyer et al. [151] for bimanual manipulation. For these reasons, the low-frequency, high-tension approximation is revised for an individual within a dyad, and the low-frequency, *low-tension* approximation [120] is applied instead (the first bracket is intentionally left blank as its content is still to be determined):

$$G_1^e(s) = [\dots] \left[\frac{e^{-\tau s}}{(1 + 2DT_\omega s + T_\omega^2 s^2)} \right]. \quad (4.13)$$

$G_2^e(s)$ is defined in analogy.

Next, the effect of haptic interaction and of the revision of the low-frequency approximation of the second bracket on the first bracket of equation (4.5) is investigated. In case of an interacting dyad, it is no longer sufficient to consider only the dynamics of the object, here, its inertia. Instead, the coupled dynamics formed by the object and the human arms have to be taken into consideration. Each partner's arm impedance is coupled into the system. Hence, the plant to be controlled is resembled by a general, second-order mechanical impedance where the inertia of the object and the human arms can be lumped as they are in parallel. However, the low-frequency approximation of the human control behavior remains unchanged despite of the changed dynamics. This is because McRuer and Jex [119] revealed that the control is structurally the same for mass-only and "second-order-impedance" plants, and it is of PD-type. Hence, the transfer functions of each individual within the dyad are given by

$$G_1^e(s) = \frac{F_1^e(s)}{E(s)} = [K(1 + T_z s)] \left[\frac{e^{-\tau s}}{(1 + 2DT_\omega s + T_\omega^2 s^2)} \right]. \quad (4.14)$$

Again, G_2^e is defined in analogy.

In summary, model transfer functions of

- 1) an individual operator (cf. equation (4.8)),
- 2) an interacting dyad (cf. equation (4.12)) and
- 3) each individual within the dyad (cf. equation (4.14))

are derived in this section to describe the dynamic reactions, i.e., the applied/external forces, to the tracking error in a compensatory tracking task. In the following, the parameters of all of these models are identified and validated by experimental data.

4.3.3 Task performance & internal forces

Besides model identification, the experimental data is analyzed with respect to the following research questions:

- The introduction of (technical or human) partners aims usually at improving task performance. Thus, it is of interest if **the introduction of a partner leads to improved task performance, i.e., deviation from the desired path, in this experiment.**
- The transfer function of each individual within a dyad is based on the modeling assumption that internal forces (tension between the partners) dominates over tension within each partner (muscle tension). This assumption cannot be checked entirely because no data referring to muscle data was available. **A characterization of the internal forces** occurring in this experiment acts as an indicator, instead.

4.4 Experiments

Details on the experimental setup, procedure and conditions are introduced in the following. The analysis of the experimental data and the respective results are presented in two parts: “Task performance & internal forces”, cf. section 4.4.2 and “Haptic object manipulation: Model identification & validation”, cf. section 4.4.3. These two parts are presented in reversed order in comparison to section 4.3. This is because one prerequisite of the dyadic model equations is an internal force built up between the partners. To check first if this assumption is valid, the analysis of task performance and internal forces is conducted before model identification and validation.

4.4.1 Setup, procedure & conditions

The experimental setup consists of two 1-dof linear haptic interfaces (designed at the Institute of Automatic Control Engineering) each equipped with 1-dof force sensors (burster tension-pressure load cell 8524-E), wooden hand knobs and linear actuators (Copley Controls Corp., Thrusttube, motor type 2504) as shown in Fig. 4.6.

The graphical representation of the compensatory tracking task is implemented in C++ and visualized on conventional computer screens. The path is visualized as a white, vertical line on a screen. As the modeling approach assumes error-correction behavior (the tracking error e as input), only the current part of the reference track is visualized to prevent a prediction of the path. Hence, a compensatory task is realized. Prediction would enable the participants to plan their actions. Probably, this could have an impact on their behavior and, then, had to be considered in the modeling approach.

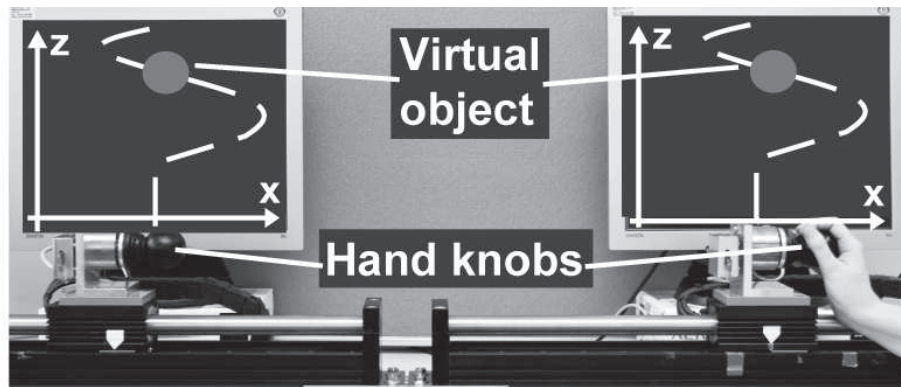


Fig. 4.6: Experimental setup consisting of two linear haptic interfaces (linked by the virtual object) and two screens with the graphical representation of the tracking path; the reference path is dashed because it is visible to the participants only at the current z-position of the virtual object, ©2009 IEEE.

The overall path length was kept constant and consists of repeated components, such as triangles, curves, straight lines or jumps (see Fig. 4.6). The order of the path components was randomized between trials to prevent learning effects. The path is scrolling down the screen with a constant velocity of $\dot{z} = -15 \text{ mm/s}$. The haptic interfaces are moved along the x -direction. Because of the z -motion of the path and its amplitude in x -direction, velocities of up to 80 mm/s are required by the participants to successfully perform the task. One trial takes $t_f = 161 \text{ s}$.

The participants were asked to follow this path as accurately as possible with a red cursor representing the inertia m_o of a virtual object. To model the mechanical properties of the virtual rigid object

$$G_o(s) = \frac{X_o(s)}{F_o(s)} = \frac{1}{m_o s^2}, \quad (4.15)$$

a position-based admittance control is applied. For more technical details on the experimental setup, please refer to appendix A.

Depending on the condition, the horizontal position of the red ball renders either the position of one haptic interface or of both haptic interfaces. In case of the partner condition, the control of the haptic interfaces is such that they are rigidly coupled. There are no extra avatars visualizing the interaction partners. But, participants were instructed such that they know that they manipulate the virtual object, collaboratively.

The following three levels of the factor interaction were introduced as experimental conditions:

1. condition “individual person with half mass” (ih),
2. condition “individual person with full mass” (if) and
3. condition “with partner” (p).

The order of conditions was balanced to compensate for sequence effects.

In the partner condition, two participants form a dyad (randomized pairing). The dyads are instructed to perform the task by moving a virtual object $m_o = 20\text{ kg}$ collaboratively along the reference trajectory. Thereby, they are linked by the virtual object. Thus, they exchange haptic signals and receive haptic feedback from the dynamics of the virtual object as well as from their respective partner. In the individual conditions, participants performed the tracking task on their own by interacting with a single haptic interface ($f_2 = 0$).

In order to keep the conditions comparable, the mass of the object should be the same whether two or one person handle it. This is because it plays an important role in terms of applied forces. Thus, in the individual condition *if*, the same virtual object with $m_o = 20\text{ kg}$ was to be moved along the reference trajectory by an individual. This condition was introduced as a baseline condition to identify the model of an individual in the present experiment. It allows to verify the applicability of the crossover-model approach under, otherwise, constant experimental conditions.

The second individual condition *ih* where $m_o = 10\text{ kg}$ was introduced for the following reason: Participants in partner trials might perform better because they share the physical workload. Hence, an increased task performance would be obtained due to a lower workload and not because of haptic interaction.

In the presented experiment, 18 participants (10 male, 2 female) took part. The participants were assigned randomly to 9 independent pairs of two. For each participant two individual trials (*if* and *ih*) and one partner trial *p* were recorded. Within each trial, the reference trajectory was repeated three times.

To standardize the test situation further the following arrangements were made: Participants not taking part in the on-going trial had to wait outside the laboratory. A wall was placed between the two participants so that they gained visual information about their partner's movements only via the virtual reality. The position (left or right seat) was randomized with the order of experimental conditions and participants. Participants used their right hand to perform the task (all of the participants are right-handed); Further, participants were not allowed to speak to each other during the experiment. White noise was played on the headphones worn by the participants, so that the noise of the moving haptic interfaces would not be distracting. Due to the simplicity of the task, there is no oral communication necessary in order to accomplish the task successfully. Hence, it is considered eligible to suppress any oral communication in order to standardize the experiment. In addition to a general instruction at the beginning of the experiment, the participants had a test-curve at the start of each trial. This curve was not part of the analysis. Participants were informed beforehand about the upcoming condition.

4.4.2 Task performance & internal forces

The experiment was conducted using this experimental setup. Next, data analysis and results of task performance and internal forces are presented.

Data analysis

Task-performance and internal-force analysis is conducted by applying the following measures.

Task performance

In order to analyze task performance in the three different conditions, the root-mean-square error between the reference path x^d and the virtual object position x_o is applied

$$RMSE_x = \sqrt{\frac{\sum_{i=1}^N (x_i^d - x_{o,i})^2}{N}} \quad (4.16)$$

where N is the the number of samples per trial.⁶ The mean $RMSE_x$ is calculated for each trial, and an ANOVA (Analysis of variance) is conducted to compare the three conditions if , ih and p .

Internal forces

The internal forces are applied as introduced in chapter 2

$$f^i = \begin{cases} f_1 & \text{if } \text{sgn}(f_1) \neq \text{sgn}(f_2) \wedge |f_1| \leq |f_2| \\ 0 & \text{if } \text{sgn}(f_1) = \text{sgn}(f_2) \\ -f_2 & \text{if } \text{sgn}(f_1) \neq \text{sgn}(f_2) \wedge |f_1| > |f_2| \end{cases} \quad (4.17)$$

where $f^i < 0$ means that the partners push against each other and $f^i > 0$ that the partners pull away from each other.

For the model identification, it is of interest if internal forces are built up between the partners. Hence, their percental occurrence in relation to the total trial length is evaluated (sample-based). Additionally, they are analyzed separately for pushing ($f^i < 0$), pulling ($f^i > 0$) or no internal forces ($f^i = 0$) by their mean values in the partner condition p .

⁶To find an appropriate measure of task performance, the experimental data was also analyzed with other performance measures like mean square error or time on target. As the qualitative results were the same for all performance measures, only the $RMSE_x$ results are reported.

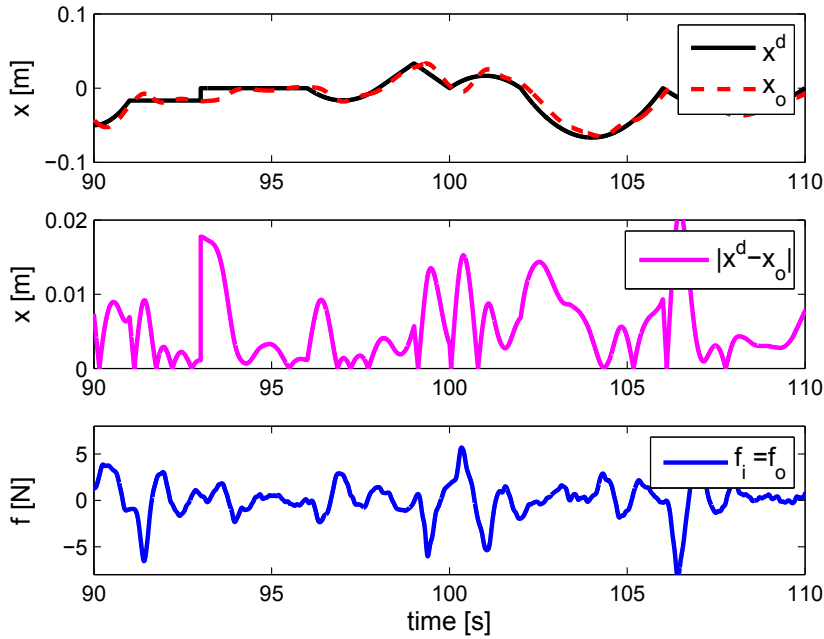


Fig. 4.7: Individual condition if : A typical measurement data set of an individual performing the task; x^d : reference trajectory; x_o , object position; $|x^d - x_o|$: deviation between reference trajectory and object position; $f_i = f_o$: applied force (=individual force)

Results

To provide a general impression of the experimental data, Fig. 4.7 and Fig. 4.8 show typical measurement data of an individual as well as an interacting dyad. These plots further demonstrate that differences between the conditions are hard to be identified by inspection only. A statistical analysis is required. The results with respect to task performance and internal forces are presented next.

Task performance

Task performance is increased for the partner condition (mean: 3.10 mm , standard error: 0.09 mm) compared to both single conditions, as depicted in Fig. 4.9. A repeated measurement ANOVA showed significant influence of the factor “experimental condition” on the performance measure ($F(2, 22) = 30, 729$; $p < 0.000$; partial $\eta^2 = 0.736$). Bonferroni-adjusted pairwise comparisons revealed a significant difference ($p < 0.05$) between all three levels (p , if , ih) of the factor. In the individual conditions, participants performed with lower $RMSE_x$ when they had to move only half the weight (mean: 3.94 mm , standard error: 0.18 mm) of the virtual mass compared to the full mass (mean: 4.68 mm , standard error: 0.18 mm).

While it is not surprising that participants showed higher performance in terms of $RMSE_x$ when dealing with lower virtual mass in the individual tracking condition, they performed

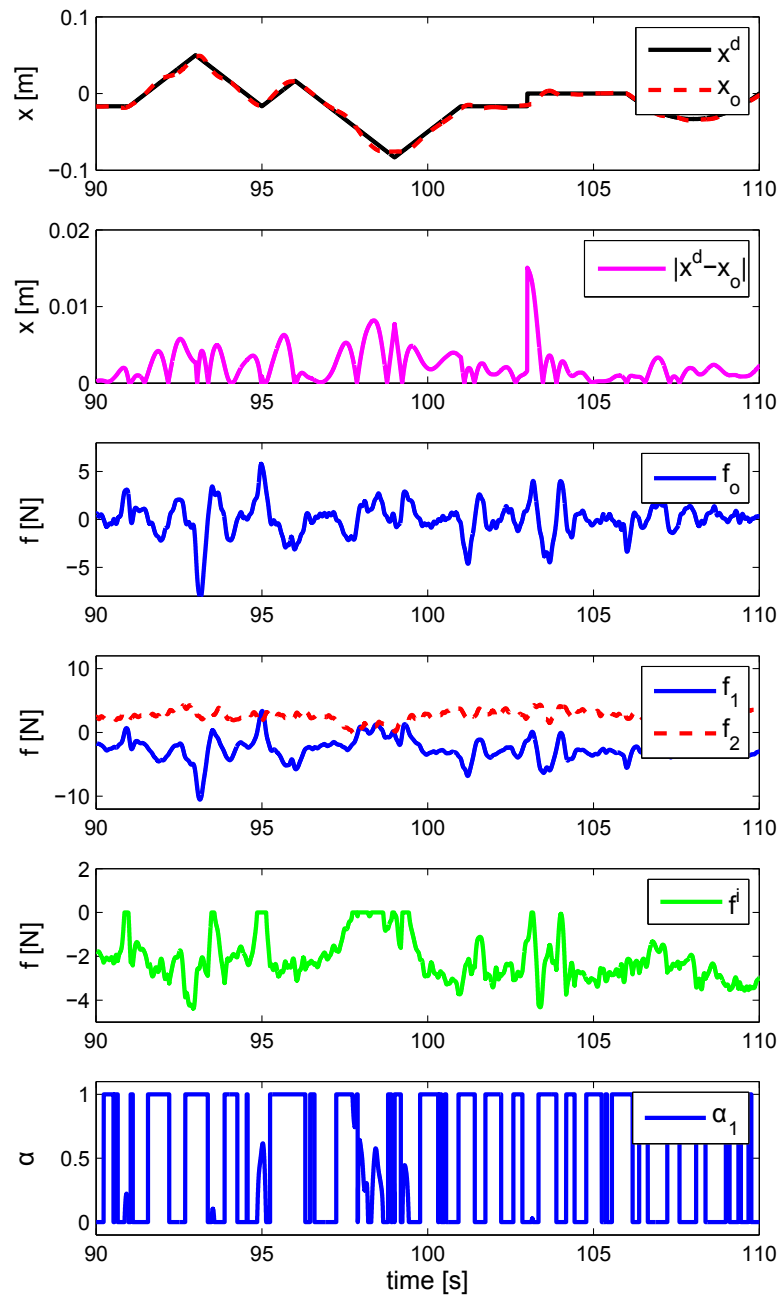


Fig. 4.8: Partner condition p : A typical measurement data set of an interacting dyad performing the task collaboratively; x^d : reference trajectory; x_o , object position; $|x^d - x_o|$: deviation between reference trajectory and object position; f_o : resulting force; f_1, f_2 : force applied by partner 1 and partner 2, respectively; f^i : internal force ($f^i < 0$: push, $f^i > 0$: pull); α_1 : workload-sharing parameter of partner 1 (partner 2: $\alpha_2 = 1 - \alpha_1$); The analysis of workload sharing is not in the focus of this experiment. However, as it is related to the internal force, the plot is reported for the sake of completeness but not further evaluated.

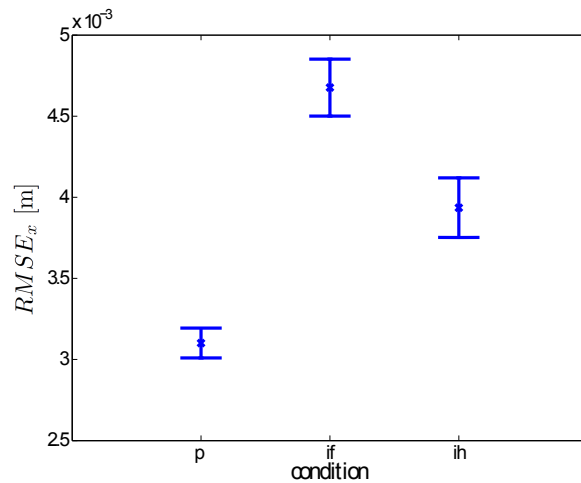


Fig. 4.9: Task performance, ©2009 IEEE: Analysis of root-mean-square error $RMSE_x$ (Mean and standard error); Lower values mean better task performance.

even better, when they interacted with a partner. Consequently, the hypothesis that the $RMSE_x$ is lower in interaction trials can be confirmed.

Internal forces

Fig. 4.8 visualizes that the interacting partners build up high internal forces that are dynamic over time. In the displayed measurement interval, the partners push continuously against each other ($f^i < 0$). The histogram in Fig. 4.10 shows another representation of the dynamics of the internal forces. It indicates that if partners push against each other, they apply on average higher forces and with a higher variance than if they pull away from each other. This is confirmed by the boxplot of the mean trial values in Fig. 4.11 and the following analysis of the mean values: If the partners push against each other, they build up on average an internal force of $\overline{f_{push}^i} = 0.822 N$ ($\sigma = 0.620 N$). If they pull away from other, the mean internal force is $\overline{f_{pull}^i} = 0.426 N$ ($\sigma = 0.168 N$). If there is no internal force, its mean and standard deviation is (evidently) $0 N$. The sign of the internal force has a significant effect on its absolute value ($F(2, 33) = 14, 75; p < 0.000$). Bonferroni-adjusted post-hoc tests show a significant difference between the absolute value of the internal force in dependence of its sign ($p < 0.05$).

On average, the partners pull away ($f^i > 0$) from each other in 24.39%, push against each other ($f^i < 0$) in 44.64% and apply no internal force ($f^i = 0$) in 30.97% of a trial. Hence, on average internal forces are built up between the partners approximately 69% of the trial.

Discussion

To evaluate the effect of haptic interaction on human behavior in a joint compensatory tracking task, task performance in single as well as partner trials is analyzed. Results are

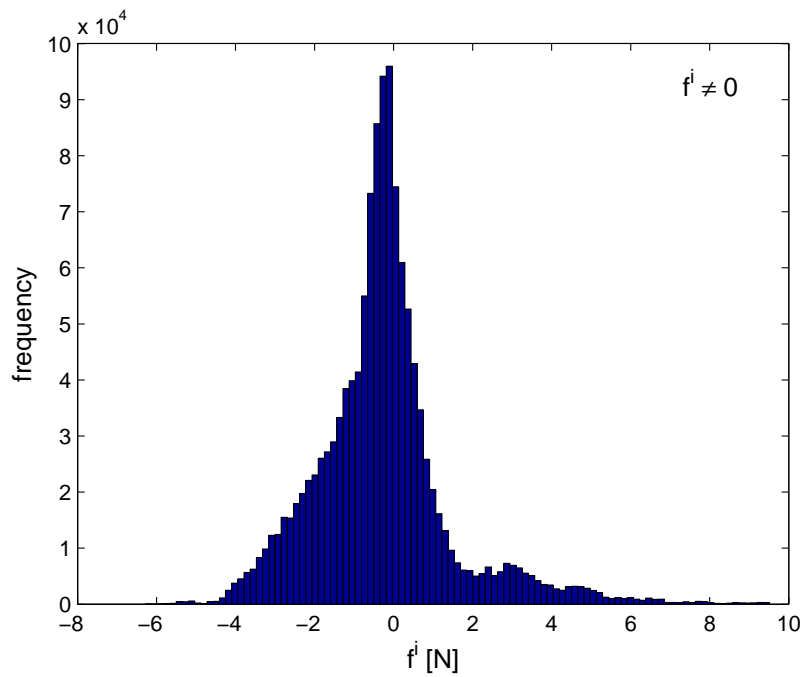


Fig. 4.10: Partner condition p : Histogram of internal forces if $f^i \neq 0$ (< 0 : push, > 0 : pull); If partners push against each other, they apply higher forces than if they pull away from each other.

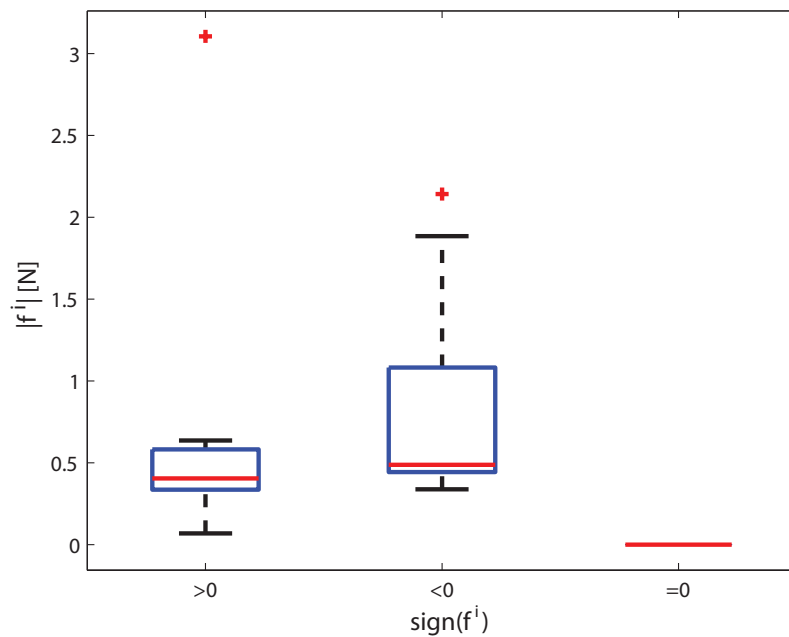


Fig. 4.11: Partner condition p : Boxplot of internal forces; $f^i < 0$: push, $f^i = 0$: no internal force, $f^i > 0$: pull); + indicates outliers.

based on three different conditions: with a partner, individual operator with the same mass as in the dyadic trials and with half of the mass. In accordance to, e.g., Gentry et al. [54], Reed et al. [149], it is confirmed that performance is increased in the partner condition. Thus, the performance-related results of pointing tasks and cyclic motions can be generalized to joint tracking tasks. This further motivates the introduction of (technical) partners in haptic tasks. As performance in the dyadic trials is even better than in the half mass trials, the performance differences in the individual and dyadic condition are due to interaction instead of the reduction of necessary individual forces.

Though not required for successful task execution, internal forces are built up in the partner trials. In Groten et al. [231] the author's research group showed for a similar experiment that on average high internal, dynamic forces are present in the partner condition. These results are confirmed by this experiment.

Participants build up significantly higher internal forces if they push against each other than if they pull away from each other. Further, internal forces are built up in most parts of the trials (in approx. 70% of each trial). This result is a first indicator that the low-frequency, low-tension approximation can be applied in the presented way for model derivation, cf. section 4.3.2.

In the displayed measurement interval of the partner condition p , the partners push continuously against each other ($f^i < 0$). A constant sign during certain intervals of the trials (either positive or negative, i.e., partners push or pull) is typical for this experiment. But, the duration of these sections differs, and no particular distribution over couples or trials could be identified (by inspection). Here, further analyses or follow-up studies are required.

In the state-of-the-art section of this chapter, two strategies discussed by Reed and Peshkin [148], Reinkensmeyer et al. [151] for a 1-dof, rotational pointing task are introduced: accelerator/decelerator and left/right. Reed et al. identified in a 1-dof, rotational pointing task that partners rather adopt an accelerator/decelerator strategy than a left/right strategy. This is related to internal forces (to be more precise, the difference force is applied there), but it is not distinguished between pushing and pulling. In Reinkensmeyer et al. [151], the results of a 1-dof rotational, *bimanual* task reveal that one hand accelerates and the other one decelerates the object. Large grasping forces are built up by the participants. A simple two-hand grasp was introduced by the experimental setup that allowed pushing-only.

As the accelerator/decelerator strategy is mainly adopted in these references and seems to describe haptic interaction behavior best, it is discussed in more detail and related to internal forces: The following definitions apply (\dot{x}_o and \ddot{x}_o are the velocity and the acceleration of the object, respectively) according to Reed and Peshkin [148]:

A partner behaves as

- | | |
|-------------|---|
| accelerator | if the object moves faster due to the partner's contribution
$f_1 > 0$ if $\ddot{x}_o > 0$ and $\dot{x}_o > 0$, or $f_1 < 0$ if $\ddot{x}_o < 0$ and $\dot{x}_o < 0$, |
| decelerator | if the objects moves slower due to the partner's contribution
$f_1 > 0$ if $\ddot{x}_o < 0$ and $\dot{x}_o > 0$, or $f_1 < 0$ if $\ddot{x}_o > 0$ and $\dot{x}_o < 0$. |

Based on this, the following conclusion is drawn: Referring to the definition of internal forces in equation (4.17) and chapter 2, the accelerator/decelerator strategy is “automatically” present if internal forces are built up between the partners. This is because

- if $f^i \neq 0$, either $\alpha_1 = 1$ and $\alpha_2 = 0$ or $\alpha_1 = 0$ and $\alpha_2 = 1$.

Then, the forces of the two partners are given by either

$$f_1 = 1 m_o \ddot{x}_o + f^i \text{ and } f_2 = -f^i \text{ or} \\ f_1 = f^i \text{ and } f_2 = 1 m_o \ddot{x}_o - f^i, \text{ respectively.}$$

Thus, only one partner contributes to the acceleration/deceleration of the object. Roles are switched, e.g., if the direction of object motion or the sign of the internal forces changes.

- if $f^i = 0$, *both* partners contribute to the object’s acceleration/deceleration according to their workload-sharing parameter (α_1 and α_2).

In this experiment, internal forces are established between the interacting partners, on average, in 70% of each trial. This implies that partners prefer to adopt an accelerator/decelerator interaction strategy in this experiment. And, the results presented by Reed and Peshkin [148], Reinkensmeyer et al. [151] for a 1-dof, rotational task as well as a bimanual task requiring wrist movements can be generalized to compensatory tracking tasks.

4.4.3 Haptic object manipulation: Model identification & validation

To examine the behavior of the interacting dyad and to compare it to a person performing the task individually, the parameters of the dynamic feedback models, cf. equations (4.8), (4.12) and (4.14), are identified in the following based on experimental data.

Data analysis

The individual conditions were introduced to validate if McRuer’s crossover model is applicable to the presented experimental setup. Therefore, the parameters of the transfer function G_i according to equation (4.8) are identified and validated for both single conditions (*if*, *ih*). Next, identification and validation of the transfer function of the overall interacting dyad G_d , cf. equation (4.12), is conducted based on measurement data of the partner condition p . Thus, it is determined if the modeling approach can be applied to haptic human-human interaction and if this approach describes the object motion when the task is conducted by a dyad. Finally, the transfer functions of the individuals within the dyads, see equation (4.14), are determined.

The transfer functions of the individual and of the interacting dyad are assumed to have the model structure according to (4.8). Their (time-constant) parameters K , T_z , T_p and τ are identified by using the measurement data of the respective experimental conditions.

The structure of the individual's behavior within a dyad is defined by equation (4.14) with the parameters K , T_z , T_p , T_n and τ to be identified from measurement data.

The horizontal error between x^d and x_o , $e(t) = x^d(t) - x_o(t)$, is the input. In the individual conditions, the applied force $f_i(t)$ and in the dyadic condition, the resulting dyadic force $f_d(t) = f_1(t) + f_2(t)$ or the external forces $f_e^1(t)$, $f_e^2(t)$ are the output, respectively. The parameter set is estimated for each transfer function and data set separately. The mean parameter sets and respective standard deviations are calculated for each condition.

All transfer functions are identified and validated by adopting the following procedure: Taking into account that the compensatory tracking path was repeated three times by each participant, the first trial was used for system identification and the two other repetitions for system validation.

Relatively high reaction times τ have to be expected because the human perception-action process takes approximately $100\text{ ms} - 200\text{ ms}$ [119]. As large time delays cause a high computational load in the identification procedure, τ is determined first by heuristics. The best fitting results were obtained for a time delay of $\tau = 120\text{ ms} \pm 100\text{ ms}$. Hence, a constant τ is applied for all models. Then, using the Matlab[®] System Identification Toolbox[™] an iterative prediction-estimation algorithm (**pem**) is applied on the shifted measurement data to identify the remaining parameters.

To address the accuracy of the model, i.e., the predictive power of the identified parameters, and to enable a comparison of the quality of the parametrized models with each other, the normalized-mean-square error

$$\text{NMSE} = \frac{\sum_{i=1}^N |f_{m,i} - f_{e,i}|^2}{\sum_{i=1}^N |f_{e,i}|^2}. \quad (4.18)$$

is calculated for each data set and the respective identified models (N : length of measurement vector). The index “ m ” indicates model data and the index “ e ” experimentally measured data. To obtain the model data, a closed-loop simulation with the reference trajectory as input and the respective transfer functions with the identified parameter sets is conducted according to Fig. 4.3 and Fig. 4.4.

To compare the dyadic model G_d and the resulting behavior of the interconnected individual models $G_{d2} = G_1^e + G_2^e$, the NMSE is not sufficient. Another measure has to be introduced for the following reason: Generally, and particularly in case of large measurement data sets, the model fit (here addressed by the NMSE) tends to increase if the number of estimated model parameters (i.e., degrees of freedom, in a statistical sense) increases. This does not imply that the predictive power of the model increases. Hence, the NMSE allows a direct comparison of models only if the number of estimated parameters (and the length of the data sets) is the same. To compare models with different structures or numbers of parameters, other means have to be chosen. Therefore, the Bayes information criterion [165]

$$\text{BIC} = \ln(\hat{\sigma}_R^2) + \frac{M}{N} \cdot \ln N \quad (4.19)$$

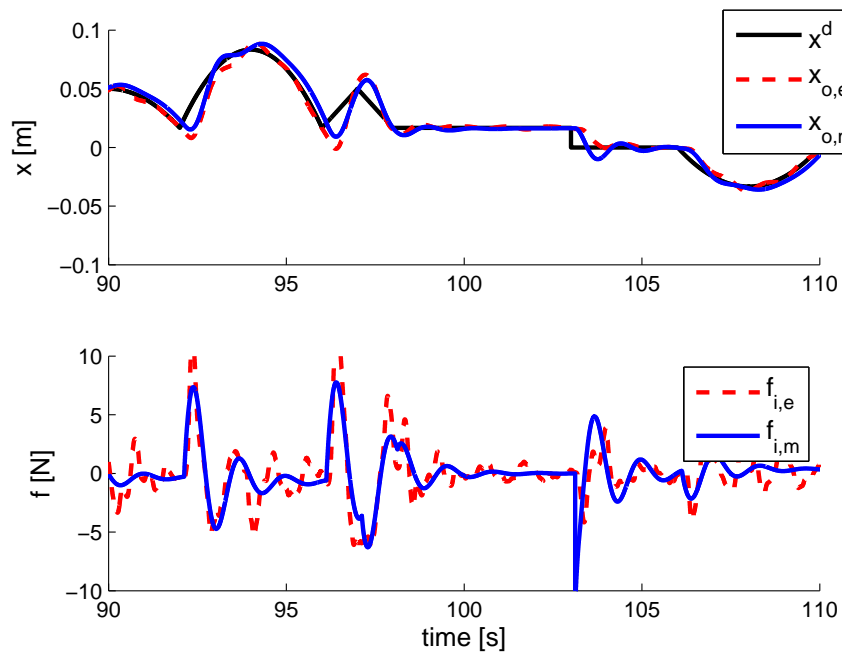


Fig. 4.12: Individual condition *if*: Comparison of one measurement data set and the respective model outputs obtained by closed-loop simulation of G_{if} ; x^d : reference trajectory; $x_{o,e}$, $x_{o,m}$: object position of experimental data and model data, respectively; $f_{i,e}$, $f_{i,m}$: applied force (=individual force) of experimental data and model data, respectively

is applied where $\hat{\sigma}_R^2$ is the variance of the residuals $R_{f,i} = f_{e,i} - f_{m,i}$, M the number of the estimated model parameters and N the length of measurement vector. The Bayes information criterion provides no information about the goodness-of-fit of each model but allows a comparison of models with a different number of parameters. If one model has a smaller BIC value than another model, this indicates that the first model explains the data better than the latter one. Finally, to address the validity of the chosen model structures, the histograms of the residuals are analyzed graphically for the partner condition to check them for normal distribution.

Results

Based on the procedure of model identification and evaluation presented in the previous paragraph, the following results are obtained for the different experimental conditions.

Individual conditions *if* and *ih*:

The models of the individual G_{if} and G_{ih} are identified and validated. The means of the estimated parameters and their standard deviations σ , averaged over the parameter sets, are presented in Tab. 4.1. Fig. 4.12 shows one typical experimental data set of an individual

in comparison to the data of the respective model G_{if} . The mean normalized-mean-square error $\overline{\text{NMSE}}$ is reported in Tab. 4.3.

The plot in Fig. 4.12 illustrates that the model describes the main characteristics of human behavior. The $\overline{\text{NMSE}}$ evaluation shows that the model fits the data in the if as good as in the ih condition. It is concluded that the crossover model approach describes the behavior of a single person in the considered scenario even if different masses are presented to the participants. In the if condition, double the inertia has to be moved compared to the ih condition. For this reason, the forces that have to be applied to correct a given tracking error are higher. This explains the increased K . The different masses have only minor influence on T_z and T_p .

Partner condition p - dyadic behavior:

The results of the parameter identification of G_d (mean and standard deviation) are presented in Tab. 4.1. The parameter T_p is in the same range in the three experimental conditions. Thus, it takes the individual operator as well as the dyads approximately the same time to correct a present deviation from the desired path. However, K and T_z of G_d differ from those of the single conditions (G_{if} , G_{ih}). The higher gain K shows, that higher forces are applied by the interacting dyad than by the single person to compensate for the same tracking error. At the same time, the smaller derivative time T_z in the partner condition indicates that the change rate of the corrective actions is smaller. Thus, haptic interaction clearly has an effect on the behavior of the interacting partners.

To illustrate the quality of the models, Fig. 4.13 shows one typical data set of an interacting dyad in comparison to data generated by the respective model G_d . The model evaluation based on the graphical plots as well as the $\overline{\text{NMSE}}$ of G_d , cf. Tab. 4.3, reveals that the transfer function's quality is the same for the dyad as for an individual operator.

Dyadic interaction condition d - individuals within dyad:

The results of the parameter identification for the individual model of each of the dyadic interaction partners is presented in Tab. 4.2. The differences of the mean parameter values of the two partners are not significant (t-test).

Similar to the previous conditions, Fig. 4.14 and Fig. 4.15 show a typical data set of an interacting dyad and the corresponding model simulation results. In Fig. 4.14, this is plotted for the external forces of both partners. In Fig. 4.15, the position and dyadic applied force is depicted. The dyadic force was obtained as the sum of the individual external forces (= model outputs in case of the simulation). These plots in combination with the $\overline{\text{NMSE}}$, cf. Tab. 4.3, show that the models of each individual within the dyad are capable of reproducing the main characteristics of each partner's external forces. These results are in analogy with those of individuals and dyads.

To compare the results of the dyadic model G_d with the model formed of the two individual transfer functions G_1^e and G_2^e , $G_{d,2} = G_1^e + G_2^e$, both the model outputs and the object positions are depicted in Fig. 4.16. It is found that the $\overline{\text{NMSE}}$ of $G_{d,2}$ is smaller than

Tab. 4.1: Model identification: Parameters of the transfer functions G_{if} and G_{ih} of the individual conditions as well as of the dyadic model G_d in the partner condition ($\tau = 120\text{ ms}$) – Mean values and standard deviations are reported.

The high standard deviation σ within each condition is explained by the fact that human behavior is modeled. Human behavior is subject to high variability because of the participant's interpersonal perception, motor system, physical state or concentration on the task.

	\bar{K} [N/m]	σ_K [N/m]	\bar{T}_z [s]	σ_{Tz} [s]	\bar{T}_p [s]	σ_{Tp} [s]
G_{if}	33.79	25.62	4.50	3.06	0.16	0.05
G_{ih}	15.98	10.00	5.29	5.47	0.13	0.02
G_d	109.82	19.85	0.86	0.09	0.10	0.012

Tab. 4.2: Model identification: Parameters of the transfer functions of each individual in the partner condition G_1^e and G_2^e ($\tau = 120\text{ ms}$) – Mean values and standard deviations are reported.

	\bar{K} [N/m]	σ_K [N/m]	\bar{T}_z [s]	σ_{Tz} [s]	\bar{T}_ω [s]	$\sigma_{T\omega}$ [s]	D [1]	σ_D [1]
G_1^e	66.62	27.33	0.68	0.21	0.07	0.01	0.40	0.10
G_2^e	36.87	21.47	3.07	6.10	0.09	0.04	0.35	0.16

Tab. 4.3: Model evaluation: Normalized-mean-square error (NMSE) and Bayesian Information Criterion (BIC)

	$\overline{\text{NMSE}}$	σ_{NMSE}	BIC
G_{if}	0.65	0.20	-
G_{ih}	0.69	0.14	-
G_d	0.70	0.19	1.79
G_1^e	0.72	0.35	-
G_2^e	0.67	0.28	-
G_{d2}	0.56	0.24	1.54

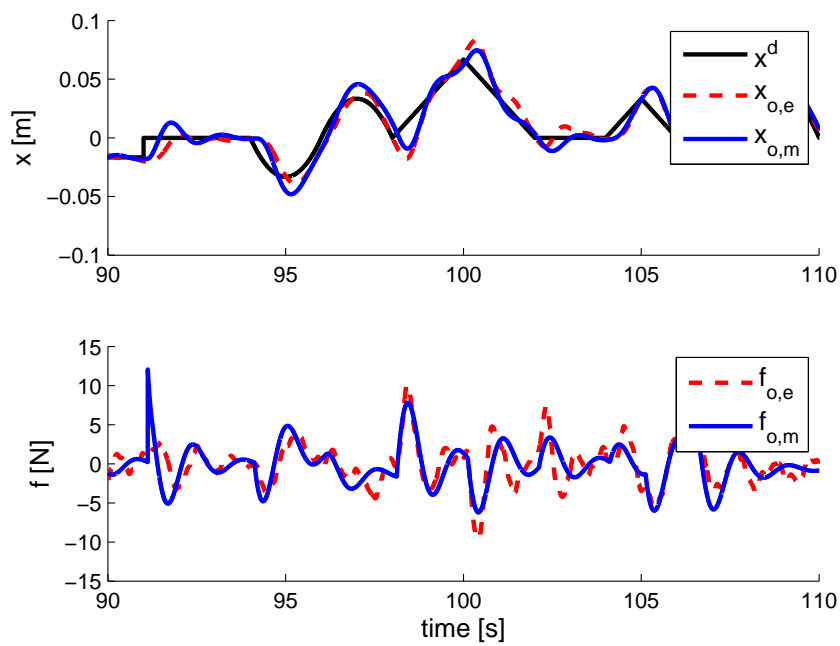


Fig. 4.13: Partner condition p - dyadic behavior I: Comparison of one measurement data set and the respective model outputs obtained by closed-loop simulation of G_d ; x^d : reference trajectory; $x_{o,e}$, $x_{o,m}$: object position of experimental data and model data, respectively; $f_{o,e}$, $f_{o,m}$: applied force (=dyadic force) of experimental data and model data, respectively; Figure adapted and redrawn from Feth et al. [224] ©2009 IEEE.

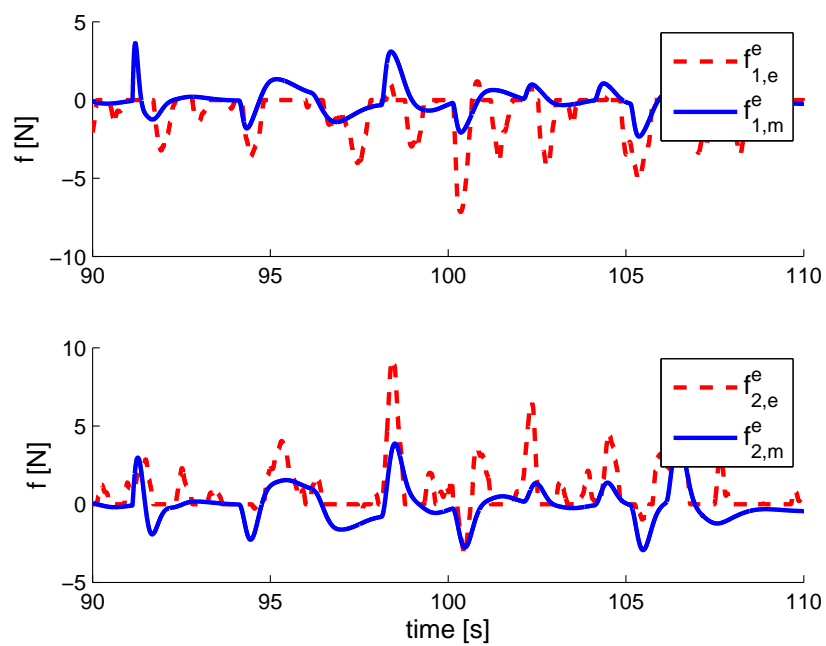


Fig. 4.14: Partner condition p - individual external forces: Comparison of one measurement data set and the respective model outputs obtained by closed-loop simulation of G_1^e and G_2^e ; $f_{1,e}^e$, $f_{1,m}^e$: external force of experimental data and model data, respectively (partner 1); $f_{2,e}^e$, $f_{2,m}^e$: external force of experimental data and model data, respectively (partner 2)

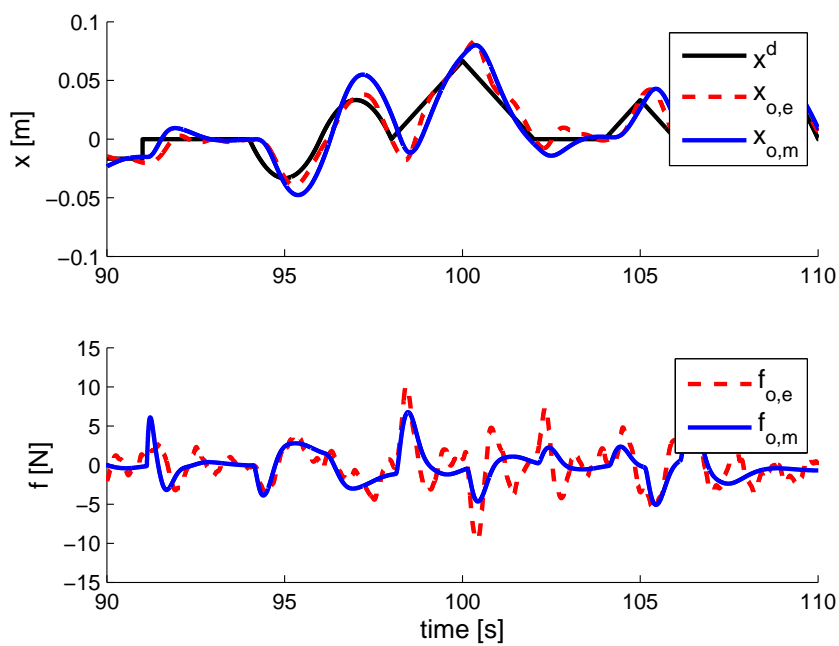


Fig. 4.15: Partner condition p - dyadic behavior II: Comparison of one measurement data set and the respective model outputs obtained by closed-loop simulation of G_1^e and G_2^e ; x^d : reference trajectory; $x_{o,e}$, $x_{o,m}$: object position of experimental data and model data, respectively; $f_{o,e}$, $f_{o,m}$: applied force (=dyadic force) of experimental data and model data, respectively; $f_o = f_1^e + f_2^e$

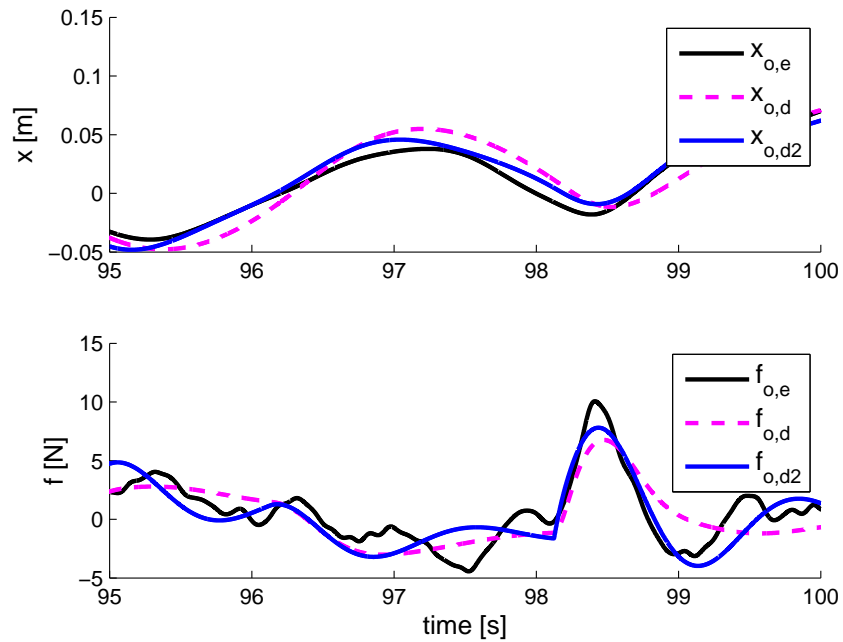


Fig. 4.16: Partner condition p - comparison of dyadic behavior I & II: Comparison of model outputs obtained by closed-loop simulation of G_d and $G_{d,2}$; $x_{o,e}$, $x_{o,d}$, $x_{o,d2}$: object position of experimental data and of the two models; $f_{o,e}$, $f_{o,d}$, $f_{o,d2}$: applied force (=dyadic force) of experimental data and of the two models

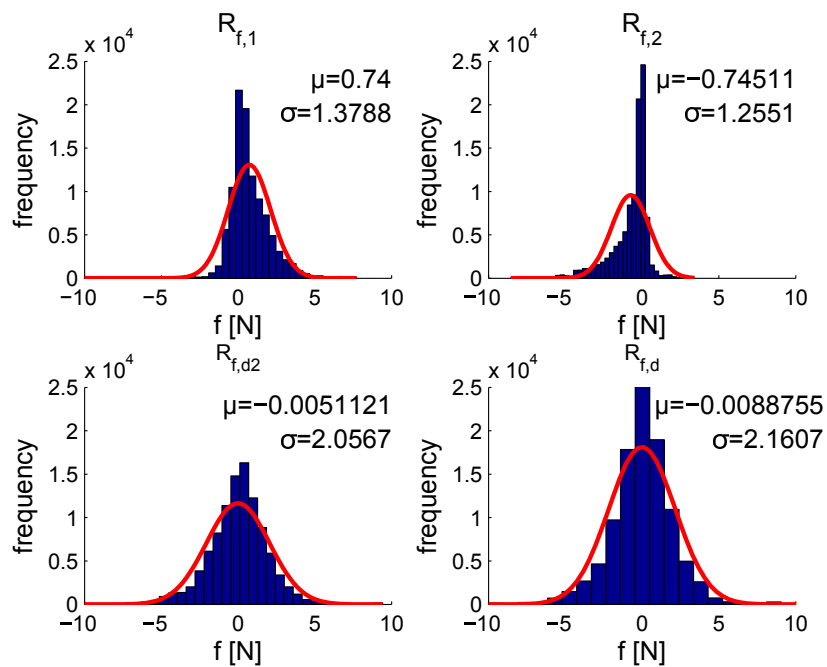


Fig. 4.17: Partner condition p - comparison of dyadic behavior I & II: Residuals of f_1^e , f_2^e , $f_{o,d}$, $f_{o,d2}$ (clock-wise starting in the upper left corner) and the estimated normal distribution

that of G_d . However, the $\overline{\text{NMSE}}$ of these two models cannot be compared because of the different number of parameters. G_d exhibits three parameters in contrast to the eight parameters of $G_{d,2}$ (namely K , T_z , T_w and D of G_1^e and G_2^e). For this reason, the Bayesian Information Criterion (BIC) is applied and reported in Tab. 4.3 for a valid comparison. Fig. 4.17 contains the respective residuals and the parameters of a normal distribution estimated from the residuals. The BIC of $G_{d,2}$ is smaller than the one of G_d (difference: 0.25). Hence, $G_{d,2}$ explains the dyadic data (slightly) better than G_d .

Discussion

Based on the measurement data obtained in a 1-dof, compensatory tracking experiment, first, the crossover model is identified and validated for an individual performing the task as baseline condition. Results show that the main characteristics of the measured forces are reproduced by the model. It is therefore concluded that the crossover model approach is applicable to the present compensatory tracking task scenario. Next, the identification and validation of the transfer function G_d for the behavior of the interacting dyad reveals that the crossover approach is as appropriate for the resulting behavior of the interacting dyad as for the behavior of a single person. In haptic interaction, the partners adapt their behavior to each other and to the plant in such a way that the overall behavior, i.e., the overall transfer function, remains constant as formulated by McRuer and Jex [119]. Hence, the application of the crossover model approach as a dyadic, dynamic action controller is as appropriate as for a single human.

Finally, the identification results and model fit of the models for each individual within a dyad show that this modeling approach not only describes the dyadic behavior but also the external forces of each of the interacting partners. The control models of the individual and the individual within a dyad have a different structure because they are based on a high-tension and low-tension assumption, respectively. Hence, it is concluded that the individual's control behavior changes in haptic interaction not only with respect to internal forces (they are added) but also with respect to the external forces. In the context of this experiment, the change of behavior is explained by the internal forces built up between the partners.

Furthermore, this result demonstrates that although internal and external forces can be controlled independently from a system-theoretic point of view, they still may influence each other. Interesting to note in this context are the findings of Reinkensmeyer et al. [151] which suggest that *“according to task-dynamical theory, grasp force and movement kinematics can be controlled independently; however, the human motor control system apparently cannot control them independently, at least for fast, accurate movements”* [151]. Similar results are presented by Gao et al. [51] for a multi-finger manipulation task executed by a human: It was shown that the internal force is coupled with the manipulation force.

A combination of the following results:

- Feth et al. [224]: the high-tension approximation of the crossover model *does not* explain the external forces of an individual within a dyad;
- This chapter: the low-tension approximation of the crossover model *is appropriate* to describe the external forces of an individual within a dyad;

indicates that the tension between the partners (internal forces) dominates over the tension within each partner (muscle tension) from a modeling perspective. Further research on this topic is required.

The focus of this chapter is on the identification of dynamic, human, haptic interaction models as control strategies for haptic, technical interaction partners and the associated analysis. In the subsequent excursus, the experimental data is discussed from another point of view.

4.4.4 Excursus: Towards an understanding of haptic, human interaction

Though, the experiment was not designed to provide an answer to the question why adding the haptic modality and introducing a partner leads to improved task performance, it is still interesting to discuss the results of the present experiment in this context. Thereby, important future directions for this related research field are identified. In the next paragraph, common explanation attempts introduced by the current literature are revised. Subsequently, a preliminary analysis is presented that is discussed in relation to the current approaches aiming at a deeper understanding of haptic, human interaction behavior.

Explanation attempts

There are various explanation attempts in literature (cf. section 4.1.1) that try to explain the general positive effect⁷ of a) collaborative task execution with a partner compared to single task execution, and b) adding the haptic modality to a collaborative task.⁸ The most important explanation attempts are summarized in the following:

- *Social facilitation*: People tend to try harder to accomplish a task successfully if there is another person in the room watching them [161].

⁷Very few studies, cf. [58], report a negative effect of adding haptic feedback on task performance. In those studies, commonly highly non-realistic haptic signals are applied.

⁸Except for the first point of social interaction, all other approaches can be summarized under *redundancy*. The resulting additional degrees of freedom relate to either physical or cognitive resources that allow to address additional goals. Similar thoughts on “ability redundancy” have been discussed by e.g., Shiflett [172] in the context of non-haptic group labor work.

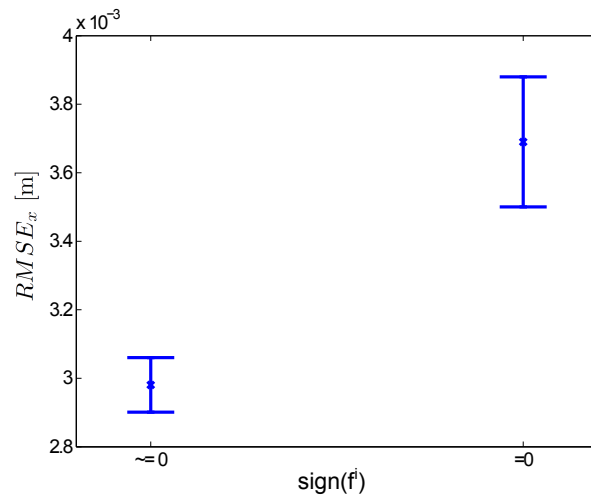


Fig. 4.18: Partner condition p - task performance in dependence of the sign of the internal force ($f^i \neq 0$ and $f^i = 0$): Task performance is significantly better if internal forces are built up between the interacting partners. Mean and one standard error are reported.

- *Reduced physical workload:* Manipulating a certain object in a desired way, the necessary overall force remains the same, independent of one or two people acting on it. In case of an interacting dyad, each partner has to apply less force than a single person to achieve the same performance, and, hence, the task can be executed with less individual physical effort. If physical effort is a critical factor for successfully performing the task (e.g., heavy object), reduced/shared physical effort is expected to increase task performance.
- *Reduced cognitive workload:* Individuals within a dyad focus on specific aspects of the task. This leads to reduced cognitive workload and allows to concentrate on certain actions.
- *Information exchange/haptic communication:* There are discussions, cf. section 3.1.3, that adaptation processes and intention negotiation are communicated between the interacting partners by a haptic language or haptic cues, often in combination with information exchange via other modalities. The identification of these processes is the main objective of *communication-* and *information-*theoretic approaches [146].
- *Human biomechanical system & muscles:* In haptic interaction, participants might constantly push and pull against each other such that their muscles are in a pre-stressed state allowing faster reactions of their motor system/muscles or lead to reduced muscle activation. Other motivations for internal forces are a mutual stabilization or an improved configuration of the biomechanical system [123, 148, 151].

Preliminary experimental analysis: Internal forces & task performance

To examine the improved task performance in the partner condition of the presented experiment in more detail, task performance is related to internal forces in the following: It is addressed if internal forces lead to increased task performance. Therefore, task performance in the partner condition p is determined for $f^i \neq 0$ and $f^i = 0$, separately.

As Fig. 4.18 shows, the tracking error is significantly (t-test: $p = 0.0023$) smaller if internal forces are built up between the partners than if no internal forces are applied. Further, the scatter plots in Fig. 4.19 descriptively visualize that there is a general tendency that the higher the internal forces are the more likely it is that the task error is small. However, the reverse tendency that a small task error relates to high internal forces does not hold.

Hence, in the limited scope of this experiment, it is concluded that internal forces not only affect the dynamic actions of humans (cf. section 4.3.2), but, in addition, they indirectly support task performance as it is significantly better in these parts of the trials.

Discussion

In the following, the results presented in the previous sections as well as the preliminary result of improved task performance if internal forces are present are discussed in the context of the above-presented explanation attempts.

Social facilitation is not addressed in the here-presented experiments. Due to the experimental design and procedure, participants always know that they are interacting with a partner, but they could not see each other. In the single conditions, their partner was also present in the lab such that the effect of social facilitation should be kept constant throughout all conditions.

Because interaction in the “partner” condition p was even better than in the “alone-half-mass” condition ih , it is concluded that the improved task performance in dyadic trials is not only a result of force reduction for the individual. Thus, if the individual’s behavior in haptic interaction is different to a single person’s behavior, this is not due to the *reduced physical workload* each partner has to apply to move the mass. Different explanations have to be considered.

If the improved task performance was caused only by a *cognitive workload* sharing, the results should be independent from the internal forces applied. However, this is not the case. Thus, although this explanation cannot be ruled out, it cannot be the only explanation for improved task performance.

The aspect of *haptic communication* is related to this. In the here-presented experiment, both partners received the same visual information about the reference trajectory and all instructions and information required for successful task execution. Hence, there is no information gradient between the partners that makes haptic communication compulsory.

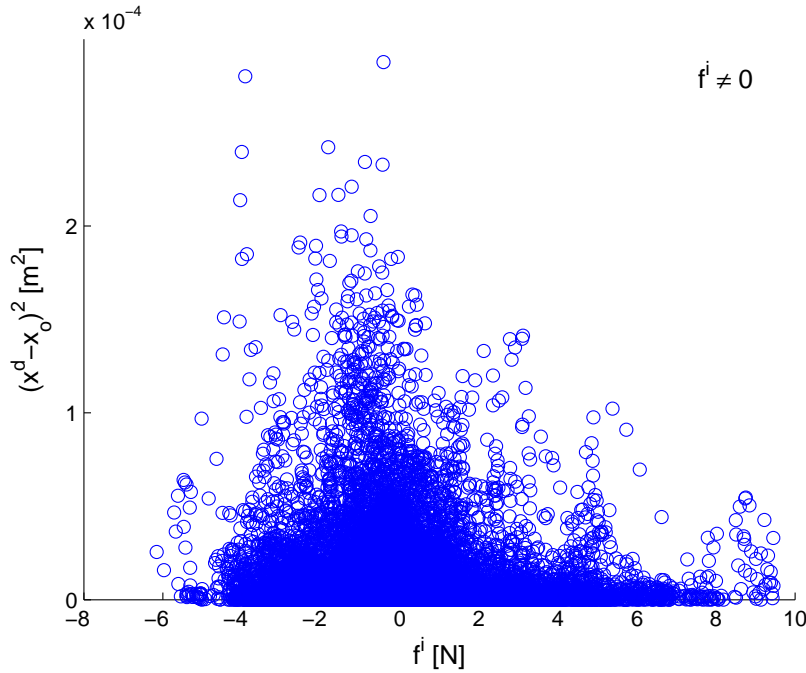


Fig. 4.19: Partner condition p - task performance over internal force: The scatter plot shows that there is a general tendency that task performance is the better the higher the absolute value of the internal force; $(x^d - x_o)^2$: task performance evaluated by the squared deviation of the reference trajectory from the object position; f^i : internal force

It is assumed that haptic communication is reduced to a minimum in this experiment. This is further elaborated in related work [232, 234].

The experimental analysis of internal forces, cf. section 4.4.2, reveals that the presented results are in line with the findings of Reed and Peshkin [148], Reinkensmeyer et al. [151] and the “accelerator/decelerator” interaction strategy. There, the internal forces are motivated by an improved configuration of the human biomechanical. Further, this improved configuration is introduced as explanation for the improved task performance observed in haptic interaction. This indicates that, though probably not the only explanation, the improved task performance in the dyadic condition of this experiment can be also explained by an improved configuration of the *human biomechanical system*. One experiment to confirm this hypothesis is, e.g., to conduct the same experiment with a condition where the participant does not interact with a real human but with a controller that controls the internal force to a fixed, still to be determined, reference force.

4.5 Conclusion

To sum up, a dynamic, task-specific control model of human, haptic interaction behavior is identified in this chapter. It forms the basis for the design of an interaction controller of

a technical partner. Additionally, an analysis of task performance and internal forces that leads towards deeper insights of haptic, dyadic interaction is presented.

To evaluate the effect of haptic interaction on human behavior in a joint compensatory tracking task, performance is analyzed in single as well as partner trials. Results are based on three different conditions: with a partner, alone with the same mass as in the interaction trials and with half of the mass. In accordance with literature, increased task performance in the “partner” condition is confirmed. **Thus, related results of increased task performance in jointly executed pointing tasks and cyclic motions are generalized to compensatory tracking tasks.**

On average, internal forces are built up between the interacting partners in approximately 70% of each trial. Furthermore, it is pointed out that **if internal forces are present, the accelerator/decelerator interaction strategy introduced in literature is adopted by the interacting partners.** Thus, as in dyadic pointing task and bimanual wrist movements, this is the preferred interaction strategy in this compensatory tracking task.

In the second part of this chapter, McRuer’s crossover approach, a well-established, task-specific, **human performance model for compensatory tracking tasks, is successfully transferred to haptic, human collaboration.** The model is applied to describe the external forces applied by the interacting partners as well as the resulting force as a function of the tracking error. Transfer functions describing the control actions of individuals, dyads as well as of each individual of the dyad are derived, identified and validated successfully by experimental data. Results of the individual conditions *if* and *ih* show that the main characteristics of the measured forces are reproduced by the model. It is concluded that the crossover model approach is applicable to the considered compensatory tracking task scenario. Next, the identification and validation of the transfer function G_d for the behavior of the interacting dyad reveals that **the crossover approach is as appropriate for the resulting behavior of the interacting dyad as for the behavior of an individual.** The identification results of each individual within a dyad show that this modeling approach describes not only the individual and dyadic behavior but also the external forces of each of the interacting partners.

Thus, the **interacting partners adapt their behavior to each other and to the task** in such a way that the interacting dyad behaves according to the dynamic behavior of the crossover model. Further, the individuals’ behavior (with respect to external forces) changes in haptic interaction not only because internal forces are added but also with respect to external forces: Instead of the high-tension approximation of the crossover model applied in the individual condition and for the dyad, the low-tension approximation is applied for each individual within the dyad. From a modeling perspective, this indicates that **the tension between the partners (internal force) dominates the tension within each partner (muscle tension)** [123, 148, 151].

In summary, **a human performance control model of an individual person performing a compensatory tracking task in collaboration with a human partner is presented for the first time** allowing a straightforward implementation on a robotic

partner. This is an important step towards the design of human-like interaction controllers for technical partners. In a next step, models of the internal forces have to be identified likewise, serving as the input to an internal-force controller.

As interaction in the “partner” condition was even better than in the “individual-half-mass” condition, it is concluded that the improved task performance in dyadic trials is not only a result of force reduction for the individual. Different explanations have to be considered. A preliminary analysis reveals that **the task error is smaller if internal forces are present**. With reference to literature, it is hypothesized that one reason for this is that the internal forces built up between the interacting partners are associated with an improved configuration of the human biomechanical system. This supports task execution which leads to increased task performance. To validate this hypothesis, follow-up experiments are required.

Combining these results towards robot control, it is concluded that task performance in haptic human-robot collaboration may be increased by control strategies that minimize the task error itself *or* by control strategies that aim at optimizing the configuration of the human biomechanical system, e.g., by an appropriate internal-force controller.

Haptic, human interaction behavior is very complex. And, as the state-of-the-art section revealed, there are only very few approaches modeling dynamic, dyadic interaction behavior, this dissertation could build on. Because of this, the results presented in this chapter were obtained in a 1-dof, highly-controlled setup to ensure conclusive results despite of the many unknowns. The control framework introduced in the previous chapter and the experimental paradigm applied in this chapter directly point out how the results of this highly-structured environment can be extended to real-world applications: for example, by iteratively increasing the complexity, by increasing the degrees of freedom, by addressing different object dynamics, by changing the tracking task or by introducing a track preview.

In particular, the extension to multi-dof scenarios is of main relevance. In this context, the findings of Marken [115] are of importance: His experimental results indicate that humans control their degrees of freedom independently. If this also holds for haptic, human collaboration, model identification and validation would be simplified a lot because it could be conducted independently for each of the degrees of freedom of a certain scenario.

Once interaction control strategies are identified, next steps involve the manipulation of the information provided to each of the interacting partners. This is related to intention negotiation and task planning. Groten et al. [232] address these aspects in an experiment where decision-making is demanded from the participants by visualizing different intended reference trajectories. In this context, beside applied, resulting and internal forces, the dominance distribution α (on a physical level directly related to workload sharing) gains importance [230].

5 Evaluation of collaborative, technical, haptic interaction partners in terms of human-likeness and task performance

A key component in the design process of interaction controllers implemented on technical, haptic partners is the evaluation of the developed approaches. Related to the respective control goals, different aspects have to be addressed by the evaluation study.

As in the rest of this dissertation, successful task execution and human-like, as one instance of intuitive, interaction behavior are in the focus of the following evaluation. It allows the developer to address the human-likeness of the robot as perceived by the human interaction partner and to derive related system requirements [168]. In order to evaluate human-likeness of a specific implementation, a relative statement in comparison to a benchmark is a prerequisite. In this way, the best out of several possible robot partner implementations can be identified within the design and evaluation process.

Recently, the evaluation of human-likeness has received broad attention in the literature. However, only few studies can be found in the field of physical human-robot interaction. Thus, the goal of this chapter is two-fold: a) general methods for evaluating the human-likeness of haptic interaction partners are established, and b) the relation between human-likeness and task performance in a typical haptic interaction task is addressed experimentally. This latter relationship is important for the development of haptic partners as the control strategies have to combine both requirements.

In the next section, related work is introduced. Based on this, several human-likeness measures are compared. They allow to evaluate different realizations of haptic interaction partners as done in the experiment. The results of this study allow conclusions on the general development of design guidelines and evaluation methods for technical, haptic interaction partners.

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5.1 Related work

The perceived human-likeness of an artificial partner's behavior is a latent psychological concept and, hence, not directly measurable. This makes its evaluation challenging, and adequate methods have yet to be found. As the design of human-like, robot interaction partners is a relatively immature field of research, such evaluations are also still in their early stages. In contrast, the evaluation of *presence* (another latent concept referring to the perceived immersion in an artificial world) when operating in virtual or remote environments is a more mature field of research. The assumption is made that methods to measure presence can be transferred or adapted to the evaluation of human-likeness. Based on this, the goal of this dissertation is to apply the knowledge of evaluation methods from the topic of presence to that of human-likeness. For this reason, a review of the relevant literature on the analysis of presence in the context of virtual environments and teleoperation systems and that on human-likeness evaluation is given.

5.1.1 Presence evaluation in virtual environments & teleoperation systems

Presence is defined as the feeling of being in a virtual or remote environment. In the context of robot, haptic interaction partners, the concept of *co-presence* which refers to the feeling of “*being together or being co-located with another person*” [164] in a remote/virtual environment, is even more closely related to human-likeness. Based on the survey of IJsselsteijn et al. [82], methods are presented that have been successfully applied to the evaluation of (co-)presence. Additionally, categories to structure these methods are defined in the following paragraphs.

Presence measures are divided into two main categories: *subjective* and *objective*, see Fig. 5.1. Subjective measures can be further divided into those which are based on a predefined scale and those which are based on comparison. If a predefined scale is given, participants rate the experimental condition as to specific characteristics on this scale. For example, participants are asked to answer presence questionnaires, such as the one established by Witmer and Singer [215], after having experienced a virtual environment. The category of comparative measures is based on the comparison of two or more stimuli. Examples of this type of approach are the methods of magnitude estimation [175] and of cross-modality matching [210]. For magnitude estimation, the degree of presence is judged directly. In cross-modality matching, the intensity of one stimulus is rated by adjusting the intensity of another modality, e.g., the more present a human feels in a virtual environment the more the participant will increase the amplitude of a tone. It has been suggested that paired comparisons can be used to build scales of attributes of several stimuli. In paired comparison experiments, see, e.g., [160] and [170], participants have to decide in which of the two experimental conditions they felt more present. Commonly, the

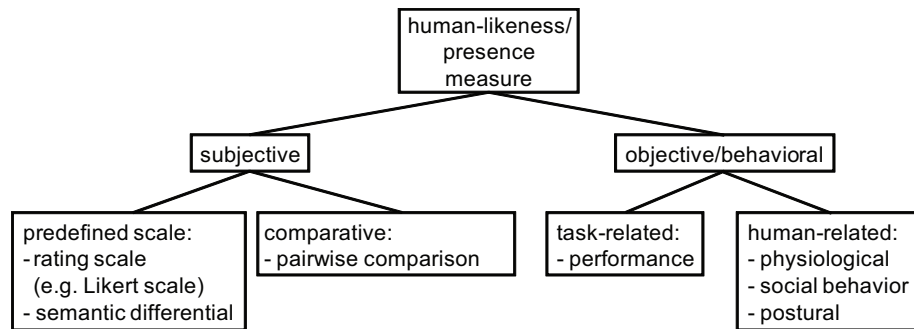


Fig. 5.1: Summary of human-likeness/presence measures based on the literature survey presented in section 5.1, ©2011 MIT Press

two compared experimental conditions are a virtual environment and a real environment, but the comparison of different virtual environments is possible as well.

Task performance [160], physiological measures, such as heart rate or skin conductance [154, 212], dual-task measures applied to address the allocation of limited cognitive/physical resources [82], social responses [82] and postural measures [49] have been proposed as objective measures. Especially, the relationship between performance and (co-)presence is subject of ongoing discussions and experiments (refer to Passenberg et al. [140] for a discussion of this topic).

5.1.2 Human-likeness evaluation of technical interaction partners

Recently, the human-likeness evaluation of robot interaction partners has gained increased attention in the literature. Although most of the studies address non-haptic interaction, some of the main contributions to this field are reviewed in the following paragraphs. The human-likeness of artificial interaction partners is commonly evaluated as a function of specific aspects, e.g., speech [35], perception [87], appearance [87, 124], motion [87, 171], behavior [34, 71, 124] or physical/haptic interaction [85, 94, 130, 148, 208].

The traditional approach to evaluating the human-likeness of a technical system is the well known “Turing test” [194]. In its original form, the participant communicates with a technical system as well as with a real human without seeing either of them. If 30% of the participants cannot distinguish reliably between the technical system and the human, the technical system “passes” the test. This method allows only discrete yes/no answers to human-likeness and, thus, provides only limited means to compare different models of robot interaction partners.

Questionnaires find frequent use in the evaluation of human-likeness [71, 85]. Participants interact with a robot partner and, later, rate its subjective human-likeness based on a predefined scale. One variation of this is Osgood’s semantic differential measure [136], e.g., as applied in Shibata and Inooka [171]. There, the participants’ ratings were based on pairs of adjectives describing attributes, e.g., human-like vs. mechanical.

A method based on social behavior patterns for objectively analyzing the human-likeness of a technical system is the measurement of a human's reaction to a specific robot. For example, in Ishiguro [87], the direction of gaze during a conversation is analyzed. This approach is based on the assumption that the more the robot is perceived to be human-like, the more naturally the participant interacts with it, e.g., eye contact in human-robot interaction would have the same patterns as in human-human interaction. Another behavioral measure is the "total Turing test" introduced by Ishiguro [87]: the time elapsed until a human can decide whether they are interacting with a human or with a robot is used as a human-likeness measure. Finally, Feil-Seifer et al. [42] mention that there are studies indicating a correlation between the degree of imitation (of a human) and task performance.

Here, the interest is in evaluating the human-likeness of a robot partner in a physical human-robot interaction task. In Ikeura et al. [85], the human-likeness of a robot using different control schemes, namely constant and variable impedance control, was analyzed based on a 5-point scale of human-likeness. In their experiment, a robot with 6 degrees of freedom (dof) was equipped with a force sensor and a handle at its end-effector. Participants were asked to move the handle in collaboration with the robot from point to point. In these conditions, the damping and spring parameters of the robot's impedance were varied. The authors measured four items: "movability", "ease of positioning", "stability" and "human-likeness" [85]. However, the robot was visible to the participants during the experiment, and interaction with a real human was not utilized as a reference condition. Details about the questionnaire and the experimental procedure were not presented.

In a parallel work performed by members of the author's research group, the effect of providing visual and haptic feedback from a virtual partner on the plausibility of social interaction was evaluated. Plausibility was judged on the basis of a 7-point rating scale while performing handshakes with a virtual partner [208]. Here, plausibility refers to the perception that an event/object in the virtual world is actually occurring/existing although it is known that it is only computer-mediated [174]. The "Turing-like" evaluation presented by Karniel et al. [94], Nisky et al. [130] deals also with the quality of social interaction in a virtual handshake scenario. They conducted a forced-choice test where the participants had to decide which of two presented models was more human-like. They analyzed their data by fitting a psycho-physical function and deriving a human-likeness measure from it. In their experiments, they addressed robot hand-shakes only, no real human condition was introduced as reference.

In Oguz et al. [133], a human-likeness evaluation of virtual haptic assistance functions in a "Haptic Board Game" is presented. The interaction with three different guidance approaches is evaluated by subjective measures with respect to "Performance", "Human-likeness", "Collaboration", "Degree of User Control" and "Degree of Computer Control". Human-likeness is approached by applying a 7-point Likert scale. Furthermore, two objective measures to evaluate task performance. However, the different measures are not related to each other. Reed and Peshkin [148] conducted a "haptic Turing test" to evaluate a feedforward force model in a 1-dof rotational pointing task. Only discrete yes/no

answers were given; the degree of human-likeness on a continuous scale was not addressed. Although not supported by a statistical analysis, they reported that subjectively almost all of the participants “*thought they were working with a person*” [148], but task performance was worse than in interaction with a real human partner. These results point out the necessity of analyzing the relation between subjectively perceived human-likeness and task performance in a more systematic way.

5.2 Proposed human-likeness measures

The previous discussion of human-likeness evaluation in haptic interaction clarifies the need for studies that introduce new measures. In order to contribute to the design-evaluation circle of haptic interaction partners, a measure of human-likeness is needed to provide the degree of human-likeness and, further, allow a comparison of different robot partner implementations with each other and also with a human. In addition, the relation between subjectively perceived human-likeness and task performance is of interest. Thus, in the following, three measures are presented: two subjective approaches to analyze human-likeness, one applying a predefined scale and one using comparative judgments, and an objective approach that evaluates task performance. These measures are derived based on a brief discussion of methods applied in the state of the art presented in the previous section.

5.2.1 Subjective predefined scale

If the subjective perception of the partner is measured using rating scales (Likert scales), the participants interact with a partner without knowing its nature (robot or human) and rate its human-likeness afterwards on a given scale. Results from those questionnaires can have a low reliability due to interpersonal differences in the underlying latent concept which introduces additional noise into the perception process. In addition, a limitation of such questionnaires is that usually no reference stimuli exist. For this reason, participants might tend to make more careful statements (*viz.*, the central tendency bias towards being less extreme within the scale offered by the questionnaire) as they do not know which conditions are still to come.

Therefore, reference stimuli are introduced in this dissertation to standardize the internal representations of the human-likeness scale prior to the presentation of the experimental conditions. These stimuli are defined by the extremes of the human-likeness scale and add a comparative component to the rating-scale procedure. This way, participants are familiar with the range of behavior they will have to judge. Please note that the extreme conditions presented as reference stimuli can, but do not have to be, experimental conditions. Through this approach, the degree of human-likeness of different robot partners can be determined and compared to each other. As the whole range of behavior from completely non-human

to “real human” lies between the two reference stimuli and is determined by them, they influence the participants’ internal human-likeness scale and have to be chosen carefully.

In the following experiment, a 5-point human-likeness scale is applied: from 1 = highly non-human/randomly-acting partner (in the following referred to as a *random* partner) to 5 = highly human-like/human partner. In the beginning, the participants are presented the two extreme conditions, *human* and *random*. Thus, the participants can relate to those baseline conditions during the duration of the whole trial.

The human reference stimulus is generated by performing the task in interaction with a real human. The lower end of the human-likeness scale is defined by a reference stimulus displaying random force signals. This is based on the assumption that a random haptic signal can be considered the opposite of a human interaction partner because it contains neither human nor interactive characteristics. It has to be noted that this definition of the lower end of the human-likeness scale is not unique, different reference stimuli and noise models could be defined.

5.2.2 Subjective pairwise comparison

In pairwise comparisons, participants always judge two conditions relative to each other, e.g., “Which condition is more human-like, A or B?”. Based on the answers of the participants, an interval scale can be derived to determine the degree of human-likeness of different robot partners and to compare them to each other. This type of human-likeness evaluation is not based on a predefined scale but on a scale generated after the experiment. Hence, it is expected that it describes the latent concept of human-likeness better than the scale used in the subjective rating. However, the number of required pairwise comparisons increases as $\binom{k}{2}$ with the number of conditions k . For the derivation of the interval scale, different methods were introduced in the literature [13, 55, 186]. In this thesis, Thurstone’s law of comparative judgment, case 5 [55, 186] is applied as introduced in appendix B.

5.2.3 Task performance

The choice of a task-performance measure is usually highly dependent on the particular task. In the present context, dealing mainly with joint object manipulations, typical task-performance measures are, e.g., task completion time, time on target and task error [89]. In the present experiment, the deviation from a desired reference trajectory is applied as the task-performance measure.

The literature on human-likeness suggests that there is a correlation between human-likeness and task performance [42]. However, the preliminary results of Reed and Peshkin [148] indicate that task performance and human-likeness are not correlated in haptic interaction. To take a first important step in finding an answer to this still open research

question, it is analyzed statistically whether, in the conducted experiment, there is a correlation between human-likeness and task performance.

In the following section, these measures will be adopted for the evaluation of two different robot partners that interact with a human in a haptic interaction task.

5.3 Experiments

The goal of the experimental evaluation described in the following subsections is to investigate the human-likeness and task performance of two different implementations of a robot, haptic interaction partner. As control conditions, two benchmark partners are introduced: a real human partner and a robot partner based on a random behavior model. The data is analyzed with all three measures presented in the previous section. In this way, the benefit of this study is two-fold: a) information can be derived on the models' appropriateness for describing human, haptic interactions, and b) the validity of the three measures and their relationships can be addressed based on empirical data. In the experiment, the participants performed the previously introduced compensatory tracking task with different, artificial or real, interaction partners.

5.3.1 Setup

The experimental setup consists, again, of two 1-dof linear haptic interfaces (designed at the Institute of Automatic Control Engineering) each equipped with force sensors (burstertension-pressure load cell 8524-E), wooden hand knobs and linear actuators (Copley Controls Corp., Thrusttube, motor type 2504) as shown in Fig. 4.6.

The graphical representation of the compensatory tracking task is implemented in C++ and visualized on conventional computer screens. The path is visualized as a white line on a screen. As the modeling approach assumes error-correction behavior (the tracking error e as input), only the current part of the reference track is visualized to prevent a prediction of the path.

The overall path length was kept constant consisting of repeated components, such as triangles, curves, straight lines and jumps (see Fig. 4.6). The order of the path components was randomized between trials to prevent learning effects. The path was scrolling down the screen with a constant velocity of $\dot{z} = -15 \text{ mm/s}$. The haptic interfaces are moved along the x -direction. Because of the z -motion of the path and its amplitude in x -direction, velocities of up to 80 mm/s are required by the participants to successfully perform the task. One trial took 40 s .

The participants were asked to follow this path as accurately as possible with a red cursor representing the inertia m_o of a virtual object. To model the mechanical properties $G_o(s) = \frac{X_o(s)}{F_o(s)} = \frac{1}{m_o s^2}$ of the virtual rigid object to be moved along the path, a position-based

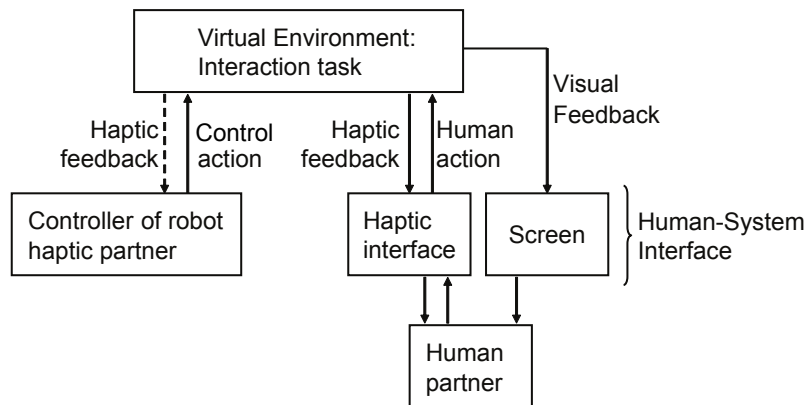


Fig. 5.2: Interaction of a human and a robotic haptic partner in a virtual environment via haptic interfaces, ©2011 MIT Press

admittance control is applied. For more technical details on the experimental setup, please refer to appendix A.

Depending on the condition, the horizontal position of the red ball renders the position of either one haptic interface or both haptic interfaces. There are no extra avatars visualizing the interaction partners. But, participants were instructed such that they understand how the virtual object is manipulated. In case of collaborating with a real human partner, the control strategies introduced in the previous chapter is applied.

If a human and the virtual representation of a haptic robot partner manipulate an object collaboratively in a virtual environment, the system structure depicted in Fig. 5.2 is typically applied. Both, the human operator's and the technical partner's actions influence the dynamics of the object. Hence, the object is manipulated with a shared control. The human is connected to the VE by a human-system interface consisting of a graphic display (e.g., computer screen, head-mounted display) and a haptic interface. The human's command signals are sent to the VE where the joint object manipulation takes place. The robot partner's command signals are generated by the controllers of the experimental conditions as introduced in section 5.3.2. Depending on the controller's structure, the robot haptic partner either reacts to the partner's behavior (bidirectional signal exchange between the partners) or not (unidirectional signal exchange). This, then, results in a high need of adaptation on the part of the user.

5.3.2 Conditions: Haptic interaction partners

In the current state of the art, the controllers of robot, haptic interaction partners are either based on feedforward or feedback approaches. This is discussed in more detail in section 3.2.3 and revised only briefly in the following.

Feedforward controllers are adopted if no disturbances are expected and the effect of a certain control command is well known or predictable. They are commonly realized by a

replay of a pre-recorded motion or force profile. In the context of haptic interaction, one example is the recording of user forces during task execution. These are, then, replayed by a robot partner. Feedforward controllers allow only for unidirectional signal exchange. The pattern replayed does not react or adapt to the behavior of the partner. Reactive behavior is, however, a key feature of haptic interaction. Hence, if the perception of human-likeness is influenced by adaptive behavior, a control strategy based on pure replay can lead to poor results in a human-likeness evaluation.

To develop robot, haptic interaction partners that can react to their (human) partner, feedback structures have been introduced. These control approaches commonly aim at maximizing task performance in a given scenario. In order to achieve a human-like behavior of the robot partner, existing feedback controllers consider the characteristics of the human perception–action loop in the design process, e.g., the time delays caused by the human information-processing system [119], the dynamics of the human arm impedance [85] or human-characteristic motion profiles such as the “minimum-jerk trajectory” [46].

In this experiment, two different kind of haptic interaction partners will be considered: one based on a feedforward force replay and the other based on a feedback structure that aims at minimizing the position error in a tracking task. To obtain a scale of human-likeness, two additional experimental conditions are introduced that define the upper and lower end of the scale: interaction with a real human partner and interaction with a random signal. More details on the haptic interaction partners are introduced in the following paragraphs.

Human partner: Interaction with a real human partner defines the upper end of our scale of human-likeness. One trained confederate interacts with all participants. This way, a standardization of behavior is achieved. This procedure is also applied by Allison et al. [5], Basdogan et al. [9], Gentry et al. [53], Khademian and Hashtrudi-Zaad [100] and Reed and Peshkin [148].

Random partner: A robot interaction partner applying random forces defines the lower end of our human-likeness scale. This unidirectional signal is neither related to task execution nor to human behavior. To avoid force patterns with only small forces and mean 0 N and to still obtain balanced forces, the random force feedback is generated based on two normally distributed signals with means $\pm 2.86\text{ N}$ and variance 4 N . The mean and variance of the two distributions were determined from the measurement data captured in Feth et al. [224], for realizing forces that are within the range of the forces typically applied by a human. The two random signals are merged by a switch which is triggered by another random signal with a Boolean output.

Feedforward-control partner (*ffw*): The feedforward controller is realized as the replay of a human force profile. The force applied by the trained confederate was recorded when interacting with another human prior to the experiment.

Feedback-control partner (*fbk*): In chapter 4, a feedback controller based on the crossover model originally introduced by McRuer and Jex [119] is identified to describe the resulting forces of an individual as well as an interacting human dyad in a 1-dof

compensatory tracking task. A quasi-linear model with the human acting as controller (see Fig. 4.3) and reacting to the current error of the actual object position is assumed. Further, time delays and lags caused by the human perception–action loop are incorporated.

The controllers of the individuals within the dyad are capable of describing the external forces only. Because of this lack of a model that fully describes the interaction behavior of an individual within an dyad, the model of the individual of condition *ih* is applied here. Hence, the simplified approach of a technical partner that takes over half the workload is realized. This is justified because the focus of the present experiment is a) on the validation of the presented human-likeness measures and b) the comparison of feedback with feedforward model approaches. Thus, based on the experimental data of 12 participants¹, the following implementation is realized as a technical feedback partner:

$$G_i(s) = \frac{18.88(1 + 4.75s)}{(1 + 0.12s)} e^{-0.12s}. \quad (5.1)$$

This general feedback model is implemented as a robot, haptic interaction partner according to the architecture shown in Fig. 5.2. The resulting robot partner allows bidirectional signal exchange between the interacting partners.

5.3.3 Participants & procedure

In the experiment, 14 participants (7 male, age = 24.13 ± 2.36 years) took part. They executed the compensatory tracking task in interaction with the four haptic interaction partners introduced in the previous section.

The participants were instructed such that they knew that they manipulated the virtual object in collaboration with a human or robot partner. At the beginning of the experiment each participant had one trial interacting knowingly with the random signal and one with the human confederate in order to build internal representations of the baseline (extreme) conditions of the human-likeness scale. In the remaining trials, the participants had no information about the conditions under which they were executing the task. Two out of the four conditions were always presented in a row. All possible pairs between the four partners/conditions (6 comparisons) were presented. In addition, the order within each comparison was repeated with the reversed order of conditions resulting in a total of 12 pairwise comparisons per participant. They were presented in random order. Participants were aware that their performance was recorded for analysis. After each pairwise comparison, participants were asked to answer two items of a questionnaire.

¹Please note that the data for model identification was collected in two lots. The second lot was collected after the present experiment was conducted. Hence, only 12 instead of 18 data set served as basis for model identification. This also explains the differences in parameters. Except for this, the exact same procedure of model identification was applied. The results reported in Feth et al. [224] are also based on the reduced data set.

To standardize the test situation, the following arrangements were imposed: A wall was placed between the participant and the confederate such that the participants did not gain visual information about the confederate’s movements. The participants used their right hand to perform the task (all of the participants were right-handed). Further, they were not allowed to speak to the confederate during the experiment. White noise was played on headphones worn by the participants, so that the noise of the moving haptic interfaces would not be distracting.

5.3.4 Data analysis

The proposed measures of human-likeness and task performance introduced in section 5.1 are now specified in the specific context of this experiment.

Subjective predefined scale: The first item of the questionnaire addressed the participant’s subjective rating of human-likeness:

How human-like was the last presented partner, on a scale of 1–5 (1: random, 5: human)?

Participants were asked to rate each condition, i.e., each of the interaction partners, three times, based on this predefined scale. The repeated presentation of the conditions caused by the experimental design increases the reliability of the questionnaire analysis. The mean of the three measurements was taken before running the statistical analysis.

Subjective pairwise comparison: The second analysis does not provide a predefined scale of human-likeness. Instead, the scale is built from pairwise comparisons. For this purpose, the second item of the questionnaire was:

Which of the two tested models was more human-like, A or B?

For each pairwise comparison, $p(S_A > S_B) = \frac{n_A}{n}$ was the proportion of the answers n_A in favor of partner A and $p(S_B > S_A) = \frac{n_B}{n}$ that of answers n_B in favor of partner B. These proportions are summarized in the matrix \mathbf{P} , which, after transformation into z -values according to (B.2), gives the matrix \mathbf{Z} . These z -values present the distance between the two stimuli. The mean of column j in \mathbf{Z} is interpreted as the human-likeness estimate of S_j . All estimates form an interval scale which can be linearly transformed to define a meaningful zero-point (here, the random condition). The analysis is conducted according to the procedure presented in Appendix B.

Relation between the predefined scale and the scale obtained by the pairwise comparisons: In order to evaluate the validity of the ratings obtained by the two subjective measures, scale-based rating and pairwise comparisons, the data is transformed. In the case of the subjective rating as well as the pairwise comparison, the human-likeness values

Tab. 5.1: Questionnaire (subjective predefined scale), ©2011 MIT Press: Mean and standard deviation (left two columns) as well as Bonferroni-adjusted pairwise comparisons between experimental conditions (right four columns), ©2011 MIT Press

partner	mean	std. deviation	p-values			
			<i>human</i>	<i>ffw</i>	<i>fbk</i>	<i>random</i>
<i>human</i>	4.000	0.636	-	0.037	0.447	< 0.001
<i>ffw</i>	3.472	0.502	0.037	-	1.000	< 0.001
<i>fbk</i>	3.667	0.348	0.447	1.000	-	< 0.001
<i>random</i>	1.750	0.780	< 0.001	< 0.001	< 0.001	-

are part of an interval scale. Hence, linear transformations can be applied: $x' = \alpha x + \beta$ [179]. The resulting human-likeness values are transformed in such a way that for both approaches the human-likeness value of the random condition is “0” and the value of the human condition is “1.”

Task performance: In addition to the subjective human-likeness measures, task performance is analyzed in the four conditions. The root mean square error is applied

$$RMSE_x = \sqrt{\frac{\sum_{i=1}^N (x_i^d - x_{o,i})^2}{N}} \quad (5.2)$$

where N is the number of samples per trial. Because each condition was tested six times to allow for the above described pairwise comparison, the mean $RMSE_x$ is calculated across all trials for each condition per person.

Relation between subjective measures and task performance: To investigate the agreement between subjective human-likeness measures and task performance, the Pearson product-moment correlation coefficient is used.

5.3.5 Results

Out of the 14 participants, two showed a decreased performance in the human and the fbk conditions compared to the remaining participants, see Fig. 5.3.

The two outliers were excluded from the analysis of the subjective measures even though they did not behave differently than the other participants. However, since the relation between the measures is of interest, it was decided that the conservative procedure (to exclude them fully) is the most appropriate here.

Subjective predefined scale: The descriptive results of the 5-point rating scale are reported in the first two columns of Tab. 5.1 and are depicted in Fig. 5.4. The human partner is rated the most human-like, and the random condition is clearly rated worse than any other partner. To investigate differences between the artificial partners, an one-

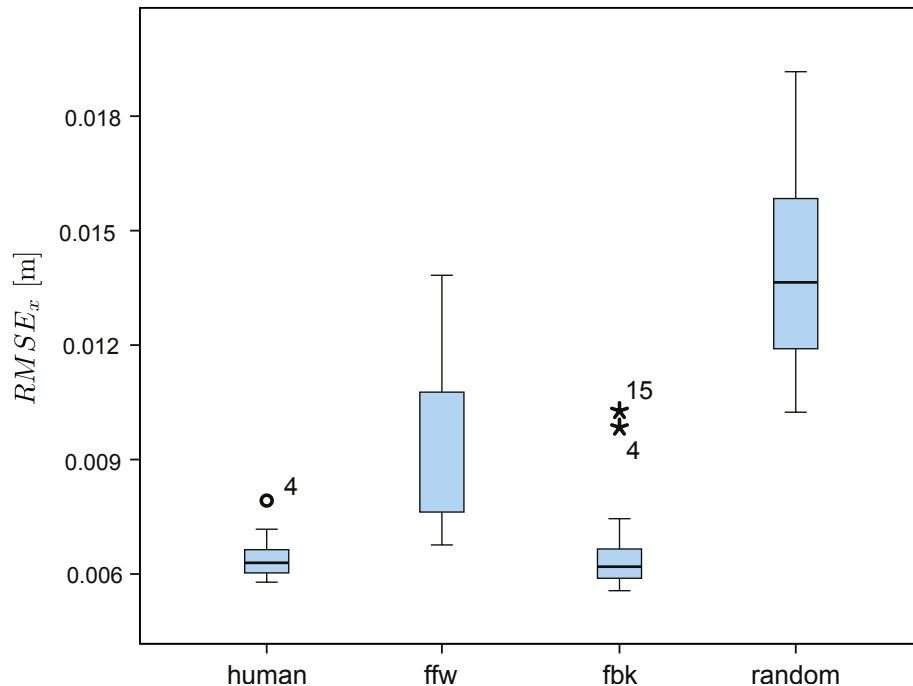


Fig. 5.3: Boxplots of the performance data in the four experimental conditions, ©2011 MIT Press: This figure shows a box and whiskers plot for the three models and the performance values. The horizontal bar in the boxes represents the median value, the box itself represents 50% of the data, and the “whiskers” embrace 100% of the data. The exceptions to these rules are marked by circles and stars. A circle represents a value which is more than 1.5 box-lengths away from the median, considered an outlier. A star represents data which is more than three box-lengths away from the median, considered an extreme outlier. The numbering of the outliers is arbitrary and is only to illustrate that two values belong to the same participant. For more information on boxplots and outliers, see, e.g., Field [44].

factorial, repeated-measurement ANOVA was conducted ($F(3, 33) = 35.146$; $p < 0.001$; partial $\eta^2 = 0.762$). A strong effect of the partner factor is revealed. Bonferroni-adjusted pairwise comparisons show that there is a significant difference between all conditions except between the fbk and the ffw, and between the fbk and the human condition, see Tab. 5.1. Still, there is a significant difference between the ffw and human condition.

Subjective pairwise comparisons: The proportions with which one partner was considered more human-like than the other in the paired comparisons were z -transformed according to the procedure described in Appendix B, see Tab. 5.2. The means of each column build the interval scale of human-likeness. To allow a more intuitive interpretation, the resulting values were transformed linearly so that the random condition serves as “0,” see Fig. 5.5. Both, the ffw and the fbk, interaction partners are considered highly human-like. The fbk interaction partner is rated more human-like than the ffw.

Relation between the predefined scale and the scale obtained by pairwise comparisons: The mean human-likeness values of the subjective rating as well as of the pairwise comparisons are transformed to fit the random condition to 0 and the human to

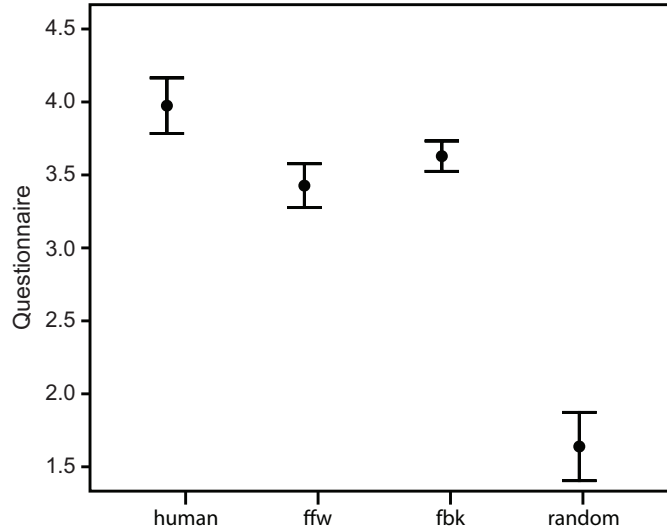


Fig. 5.4: Questionnaire (subjective predefined scale), ©2011 MIT Press: mean and one standard error of the 1-5 scale of human-likeness (5 = human) for the four experimental interaction partners, ©2011 MIT Press

Tab. 5.2: Observed frequencies with which the condition of the row is rated more human-like than the one of the column (left half) and Z -transformed values (Z -matrix) of the matrix P according to equation (B.2) (right half). The resulting human-likeness scale is a linear transformation of the column means, ©2011 MIT Press.

partner	Observed frequencies				Z -matrix			
	<i>human</i>	<i>ffw</i>	<i>fbk</i>	<i>random</i>	<i>human</i>	<i>ffw</i>	<i>fbk</i>	<i>random</i>
<i>human</i>	-	21	20	26	-	-0.67	-0.57	-1.46
<i>ffw</i>	7	-	12	26	0.67	-	0.18	-1.46
<i>fbk</i>	8	16	-	27	0.57	-0.18	-	-1.80
<i>random</i>	2	2	1	-	1.46	1.46	1.80	-
			column mean		0.90	0.20	0.47	-1.57
			scale values		2.47	1.77	2.05	0.00

1 using $x' = \frac{1}{2.25}x - 0.778$ and $x' = \frac{1}{2.47}x$, respectively. The results in Tab. 5.3 show a high agreement. The human confederate is always rated the most human-like and the random the least human-like. Furthermore, in both methods, the artificial, haptic interaction partners are rated highly human-like and the ffw model is rated less human-like than the fbk.

Task performance: Task performance is analyzed by the $RMSE_x$. The values are reported in Tab. 5.4 and are illustrated in Fig. 5.6. A one-factorial repeated ANOVA on the performance measure showed a strong, significant effect of partner on performance (Greenhouse-Geisser-adjusted: $F(3, 33) = 91.770$; $p < 0.001$; partial $\eta^2 = 0.893$). The human shows high task performance and the random partner low task performance. Bonferroni-adjusted post-hoc tests state that all comparisons are significantly different except for the human and the fbk partner, see Tab. 5.4. Thus, the fbk partner leads to

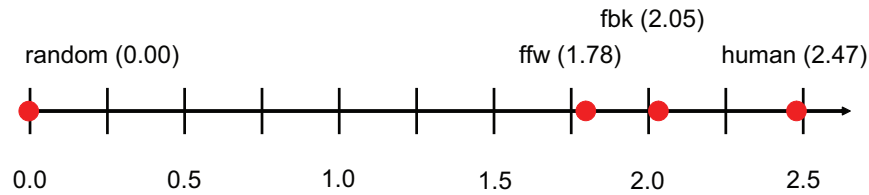


Fig. 5.5: Human-likeness scale based on Thurstone's pairwise comparison, ©2011 MIT Press

Tab. 5.3: Comparison of the human-likeness scale obtained by a predefined scale-based rating with the scale derived from pairwise comparisons (values are transformed to the interval $[0;1]$), ©2011 MIT Press

	<i>human</i>	<i>ffw</i>	<i>fbk</i>	<i>random</i>
subjective rating	1.00	0.765	0.852	0.00
pairwise comparison	1.00	0.718	0.827	0.00

performance that is similar to that of interacting with a real human whereas the *ffw* and, especially, the *random* condition lead to poorer results.

Relation between the subjective measures and task performance: To investigate the agreement between performance and human-likeness measures, the $RMSE_x$ is correlated with the 5-point rating scale answers. The Pearson correlation ($r = -.667$; $r < 0$ because higher $RMSE_x$ corresponds to lower task performance) is significant ($p < 0.001$) and large, according to Cohen [22]. Fig. 5.7 illustrates this correlation. The Pearson correlation coefficient can itself be interpreted as a measure of the size of the effect [22]. Then, $r^2 = 0.44$ (coefficient of determination) describes how much variance is explained by this effect out of the total variance [44]. Hence, in the present experimental data 44% of the overall variance in the $RMSE_x$ measure is accounted for by changes in the subjective scale and vice versa (without implying any causal relationship).

Please note that the human-likeness values obtained by the pairwise comparisons are not used for the correlation because this would require a Thurstone scale for each participant and, hence, an analysis of the data on the individual level. As this chapter aims at deriving general guidelines on the population level, the focus is on obtaining data from different participants rather than introducing a large number of repetitions for each participant. However, due to the high agreement in the results on both subjective scales, the correlation is expected to be very similar.

5.4 Discussion

The evaluation of two robot, haptic interaction partners (feedforward, feedback) contrasted to a real human partner and a partner showing random behavior leads to different results than those presented in Reed and Peshkin [148] where only discrete yes/no answers on human-likeness could be given in a “haptic Turing test”. There, the *ffw* model based

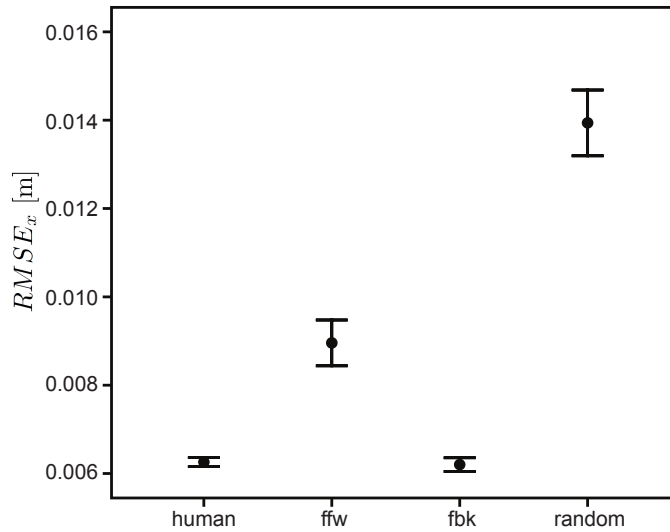


Fig. 5.6: Performance measure ($RMSE_x$: deviation between red cursor and reference path) for the four experimental partners, ©2011 MIT Press

Tab. 5.4: Performance ($RMSE_x$ in mm), ©2011 MIT Press: Mean and standard deviation (left two columns) as well as Bonferroni-adjusted pairwise comparisons between experimental conditions (right four columns)

partner	$RMSE_x$		p-values			
	mean	std. deviation	<i>human</i>	<i>ffw</i>	<i>fbk</i>	<i>random</i>
<i>human</i>	6.257	0.353	-	0.002	1.000	< 0.001
<i>ffw</i>	8.957	1.798	0.002	-	< 0.001	< 0.001
<i>fbk</i>	6.202	0.539	1.000	< 0.001	-	< 0.001
<i>random</i>	13.940	2.580	< 0.001	< 0.001	< 0.001	-

on a replay was perceived to be human-like. It is supposed that applying this binary “haptic Turing test” in the present experiment would have led to a similar result because participants rated the ffw condition highly human-like. Hence, if confronted with only two rating options, they might decide for “human-like” than against it. In the here-presented experimental study, a more differentiated rating was possible, revealing that there is room for improvement of feedforward models. In another aspect, the results found in Reed and Peshkin [148] can be replicated as in both studies the performance is better with a real human partner. This is explained by the feedforward model’s inability to react to errors made by the human.

Further, the human-likeness of a feedback model is evaluated. Although the difference is not significant, the mean values of the predefined scale-based ratings as well as the scale obtained by pairwise comparisons suggest that the fbk condition is perceived to be less human-like than a real human but more human-like than the ffw. Jagacinski and Flach [89] discuss, with reference to Krendel and McRuer [105] and McRuer et al. [121], that human actions are generated by a combination of feedforward and feedback control.

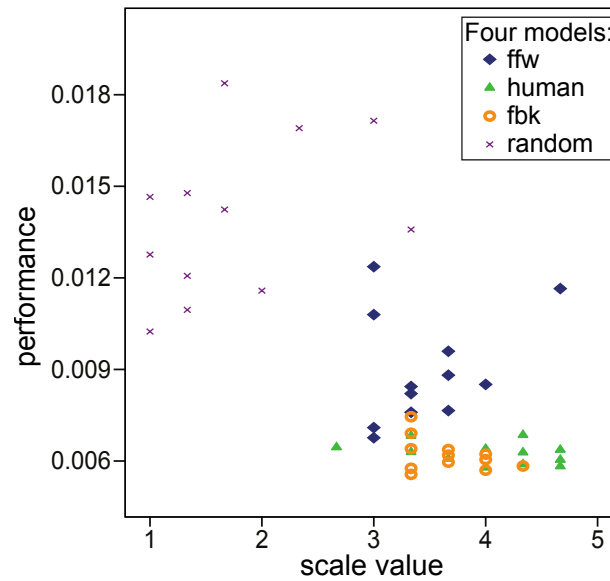


Fig. 5.7: Comparison of human-likeness (subjective scale-based rating; 1=not human-like, 5=human-like) and performance ($RMSE_x$; high $RMSE_x$ means low performance) data: Scatter plot, ©2011 MIT Press

Hence, a combination of feedforward and feedback models is suggested to further increase the human-likeness of robot, haptic collaboration partners.

Furthermore, task performance in the fbk condition is as good as with a real human partner because the feedback structure can react to errors of the interaction partner and, hence, supports task execution by corrective actions. On the restricted basis of the current experiment, it is therefore recommended that advanced robot partners designed to support task performance should provide feedback characteristics.

Due to the high level of agreement between the experimental results of the two subjective human-likeness measures (viz., the predefined scale and the scale derived from pairwise comparisons), the two reference stimuli, human and random, are considered to be appropriate as the extremes of the predefined human-likeness scale and the resulting ratings of the two robot, haptic interaction partners to be valid.

The correlation between the subjective human-likeness measures and task performance is significant and large. Therefore, the two scales are not independent. However, only 44% of the variance of one measure is described by the other. Hence, it is concluded that for a profound evaluation both scales should be addressed separately until the relation is clarified.

5.5 Conclusion

In this chapter, **new ways for an experimental evaluation of haptic, technical partners with human-like characteristics** are introduced. Therefore, existing literature on human-likeness and presence measures is reviewed, categorized and transferred to human-robot collaboration. By this and the introduction of a real human as a reference stimulus, **different control implementations can be compared on a continuous human-likeness scale**. In addition, the gap of each implementation to realistic human behavior can be analyzed. The potential for future improvements can be identified.

Two subjective **human-likeness measures** are proposed: a predefined scale and one based on pairwise comparisons. Additionally, task performance is analyzed to take account for both key requirements of haptic collaboration, performance and intuitive, here human-like, interaction. All three measures allow a **systematic comparison of different robot partners** but have not been applied together before.

The applicability and validity of the two proposed human-likeness measures is demonstrated by applying them successfully in an experiment in order to evaluate two different implementations of haptic interaction partners, a feedforward and a feedback control model. Due to the high correlation of the two subjective human-likeness measures, it is concluded that for future experiments it is sufficient to apply only one of the two approaches presented. The significant correlation between human-likeness and task performance shows that these two concepts and, thus, the respective control goals are not independent. Further research is required to gain a deeper understanding of this relation. For instance, new insights could be obtained by addressing this relation not only on a population/sample size level but also on the level of an individual human or by applying non-linear functions or by defining different task-performance measures.

This study is considered as a first approach to identify the relevant characteristics of a robot, haptic interaction partner. The experimental results show that a feedback controller is perceived to be more human-like than a feedforward controller but not as human-like as a real human. However, performance in the “feedback condition” is as good as if two human partners interact. Based on this, the development of **a combined feedback-feedforward approach** is suggested for the framework’s interaction controller module to close the gap between their perceived human-likeness and that of a real human partner. In summary, this approach allows not only the assessment of the implementations under consideration but, further, shows how results of evaluation studies contribute to the derivation of guidelines for future interaction partners.

6 Overall conclusions & future directions

This dissertation approaches the systematic controller design and evaluation of technical partners with human-like characteristics. It aims at intuitive interaction behavior in haptic human-robot collaboration. Major steps towards this goal are taken in form of the contributions presented in the following. This leads to potential future research directions discussed in the subsequent part of this chapter.

6.1 Concluding remarks

Applying an integral approach for the controller design and evaluation of haptic, robot collaboration partners in joint object-manipulation tasks, this dissertation extends this research field by the following main contributions.

A solution for a **1 degree-of-freedom, dynamic model** of the closed kinematic chain formed by two haptically interacting partners and their joint object is derived from the current state of the art of multi-robot haptic interaction. The model is established for 1-dof scenarios because these are in the focus of this dissertation. However, an extension of the presented model to multi-degrees-of-freedom tasks is straightforward as pointed out in related literature.

The control-relevant variables internal forces, external forces, resulting force, workload sharing and their relation to each other are introduced. **Unlike other approaches, the focus is broadened from object motion and the therefore-required force to the interaction between the partners.** This allows for a more intuitive interpretation of the underlying processes of haptic collaboration, forming the basis for robot controller design in haptic human-robot interaction. It is further shown that, in contrast to robot-robot interaction, a robot is not capable of controlling all involved variables, i.e., the resulting force required for object motion, internal forces and workload sharing, to a desired reference value in human-robot interaction. Hence, in the design of robot controllers for haptic human-robot collaboration, the control goals have to be carefully traded-off in order to achieve feasible and controllable interaction states. Though, derived in the context of joint object-manipulation tasks, these findings strengthen the necessity to address interactive tasks and human-robot collaboration as an independent field of research that requires solutions of its own.

Task performance, coordination (related to effort/workload sharing) and haptic communication are identified as **key control objectives** in haptic human-robot collaboration.

They can be optimized with respect to different values, such as efficient task execution or human-likeness. Here, it is important to note that human-likeness is not introduced as an independent control objective but as a “target value” of different control objectives.

Subsequently, a new, **generic control architecture** for a robot, haptic collaboration partner is set up of different modules with distinct interfaces. It is derived in the context of joint object-manipulation tasks but can be applied to a broad range of haptic human-robot collaboration scenarios. The reason for this are the generic formulation of the requirements the framework is based on, its hierarchical structure as well as the definition of one main control loop.

In combination with the respective control objectives, an unprecedented classification of related work according to the control framework’s subsystems is presented. By this, **the state of the art is integrated with the framework** such that synergetic effects can be exploited by a systematic combination of different approaches. Furthermore, this classification allows for the formulation of future research challenges as well as a systematic, modular design of advanced haptic collaboration partners. All of the subsequent chapters are embedded into the control framework.

Next, McRuer’s crossover approach, a well-established, task-specific, human performance model for compensatory tracking tasks, is successfully transferred to haptic, human collaboration behavior. The model is applied in a 1-dof, compensatory tracking task to describe the external forces applied by the interacting partners as well as the resulting force as a function of the tracking error. Dynamic modeling of haptic, human interaction behavior is very complex with many open questions. Because of this, the results presented in this dissertation were obtained in a 1-dof, highly-controlled experimental setup to ensure conclusive results despite of the many unknowns. However, due to the integration into the framework as well as the adaptation of an experimental paradigm, a discussion of the results in a generic context is ensured.

Transfer functions describing the control actions of individuals, dyads as well as each individual of the dyad are derived, identified and validated successfully by experimental data. Hence, a **human performance control model of an individual person performing a compensatory tracking task in collaboration with a human partner** is presented for the first time allowing a straightforward implementation on a robotic partner.

The results further show that the interacting partners **adapt their behavior** to each other and to the task in such a way that the crossover model can still be applied to the interacting dyad. It is also shown that the individual’s behavior changes when interacting with a partner in contrast to performing the task alone. Referring to literature, it is discussed that the change in behavior is likely to be related to the internal forces built up between the interacting partners. In more detail, the results indicate that the tension between the partners (internal forces) dominates the tension within each partner (muscle tension) with respect to the modeling of the human, dynamic control behavior.

With reference to related work, it is discussed that these internal forces are associated with an improved configuration of the human biomechanical system supporting task execution, leading to increasing task performance. Though, not in the focus of this experiment, the presented results as well as a preliminary analysis of **task performance in dependence of internal forces**, support this hypothesis and are in line with the current literature. However, for a more profound conclusion further research is necessary.

To complete the process of controller design, **new means for an experimental evaluation of haptic technical partners with human-like characteristics** have to be established. Therefore, human-likeness measures introduced in related literature are reviewed, classified and transferred to the field of haptic human-robot collaboration. Thereby, a relative statement in comparison to a benchmark condition, such as interaction with a human partner, is defined as a prerequisite. Only by this, a systematic comparison of different implementations with each other is enabled on a **continuous scale of human-likeness**. The applicability and validity of the two proposed human-likeness measures is demonstrated by applying them, successfully, in an experiment to evaluate two different implementations of haptic interaction partners. The experimental results suggest that a feedback controller is perceived to be more human-like than a feedforward controller but not as human-like as a real human. Task performance is analyzed to take account for both key requirements of haptic collaboration, performance and intuitive, here human-like, interaction. This analysis shows that performance in the “feedback condition” is as good as when two human partners interact. Based on this, the **development of a combined feedback-feedforward approach** is suggested. Furthermore, a significant correlation between human-likeness and task performance is revealed. In a first step, this shows that these two concepts and, thus, the respective control goals are not independent. Further research is required to gain a deeper understanding of this relation. In summary, this approach allows not only an assessment of the implementations under consideration but shows further **how results of evaluation studies contribute to the derivation of guidelines** for future interaction partners.

6.2 Outlook

The results and conclusions of this dissertation pave the way for multiple directions of future research. These are briefly laid out in the following section. Subsequently, a closer look is taken at one subsystem of the control architecture established in chapter 3 – the interaction controller: A new control structure for it is derived based on the presented results and conclusions. This is to make evident this thesis’s impact on future research by one, significant example.

6.2.1 General perspective

The physical, dynamic model presented in this dissertation allows for an intuitive interpretation of interaction-relevant control variables. It forms the basis for their determination. Based on a discussion of the model in the context of significant examples, it is revealed that a simultaneous control of all interaction-relevant variables is not feasible. Thus, the controller design for collaborative partners requires a profound system-theoretic analysis of the presented model, addressing the 1-dof as well as a multi-dof solution. Therefore, established methods that enable an analysis of stability, controllability and observability have to be adapted to haptic collaboration. Or, new approaches have to be identified and established in line with the results of this dissertation.

The identified control objectives as well as the subsequently-introduced, generic control framework pave the way for a systematic controller design of advanced haptic, technical collaboration partners. Due to the modular structure of the control architecture, future controller design can be focused on the different subsystems, like intention negotiation or task planning, considering always the trade-off to be made between the different control objectives. It further allows to exploit synergetic effects and the integration and combination of established and new approaches. Furthermore, due to its generic approach, its applicability is not restricted to joint object-manipulation tasks but can be extended to the wide field of haptic human-robot collaboration by implication.

The identified human performance models in a dyadic compensatory tracking task describe the external and resulting forces as a function of the tracking error. Consequentially, equivalent models of the internal forces have to be identified to enable a complete, human-like interaction controller. Therefore, further analysis of the internal forces is necessary to gain a deeper understanding of its underlying processes. In particular, the relation of tracking error and internal forces and the possible causes have to be addressed in more detail.

The presented human performance models are the first of their kind in the field of human-like control strategies in haptic collaboration. They describe the main characteristics of human behavior. Still, other control approaches, like optimal control strategies or adaptive control laws, have to be addressed in the same systematic way. The results

have to be compared with each other in order to identify the best control method in this context. Then, important next steps are the extension from one degree of freedom to multiple degrees and to move from highly-controlled lab conditions to real-world tasks. A systematic approach of this challenge is enabled by the presented control framework and experimental paradigm. By this, it is directly pointed out how to move from this highly-structured environment to real-world applications. Furthermore, the experimental results of Marken [115] suggest that humans control their degrees of freedom independently. Assuming this holds for haptic, human collaboration, model identification and validation could be conducted independently for each of the degrees of freedom in a certain scenario.

Additionally, one more direction of future research in the context of human performance models is to be mentioned here. The new insights about human performance models contribute not only to improved performance of autonomous robots but allow also valuable improvements of control algorithms in teleoperation systems. First steps in this direction were already taken in Feth et al. [226, 227, 229].

After the development of further haptic control strategies and their implementation on robotic systems, they have to be systematically evaluated. The methods introduced and applied in this dissertation provide profound information on how to execute those evaluation studies and the formulation of advanced guidelines leading to an iterative improvement of technical, haptic collaboration partners.

Summing up these future directions, the strength of an integral approach of haptic human-robot collaboration and the impact of this dissertation's results on this field of research are clearly shown. It has proven to be a suitable way to realize robot partners for intuitive haptic human-robot collaboration. By this, the quality of haptic human-robot interaction is improved sustainably.

6.2.2 A closer look at the interaction controller: A novel control structure

As the literature review in section 3.2.3 reveals, many different control architectures are suggested for the control framework's interaction controller. But, most suggested control structures solve one specific problem or are restricted to a certain type of controller or interaction strategy. Furthermore, the interdisciplinary aspects of haptic human-robot collaboration and the importance of achieving "intuitive interaction behavior" are considered only to a limited extent. These gaps are closed by the following, **new control structure of an interaction controller** by integrating the special characteristics of haptic human-robot collaboration. It is derived by fusing the previously-presented related work with the findings and conclusions of this dissertation.

Beside perceived environmental feedback, the input to the interaction controller is the desired interaction strategy, trajectory or force profile. These inputs are determined in the interaction planner based on the control objectives, cf. section 3.1. As illustrated in

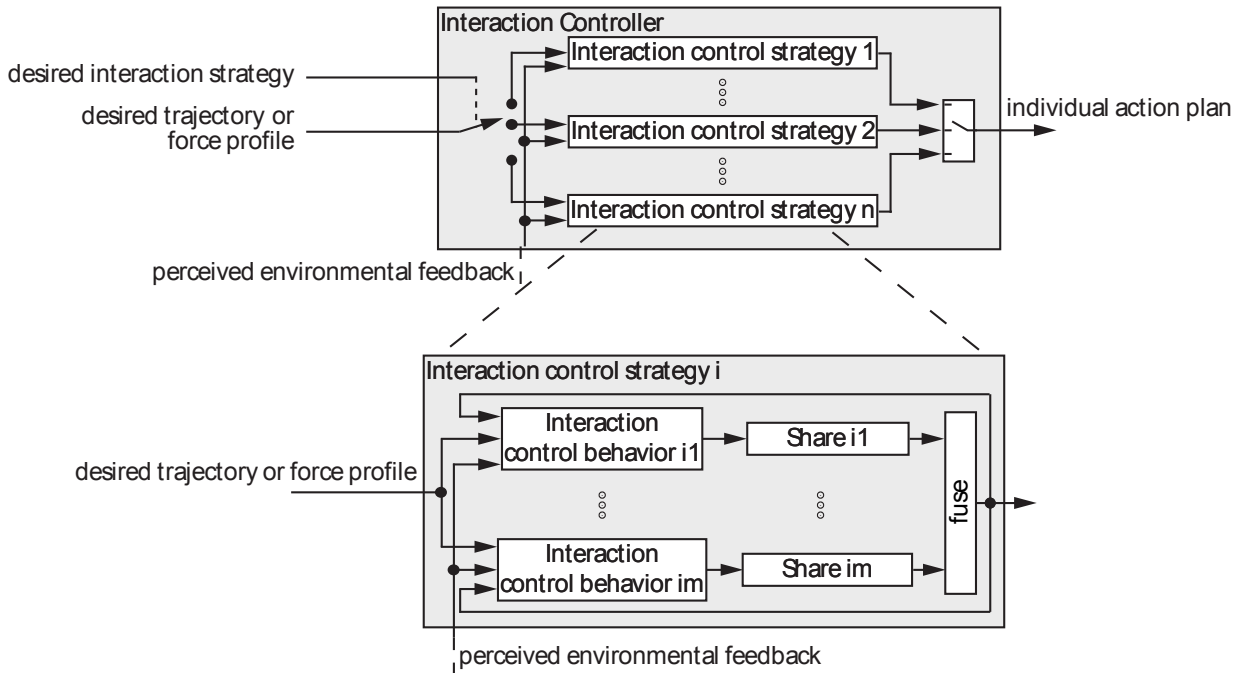


Fig. 6.1: Structure of the proposed interaction controller: The input are the desired trajectory or force profile and the interaction strategy. Based on the interaction strategy, the respective active control strategy is determined out of $1 \dots n$ available. Each interaction control strategy consists of m basic interaction control behaviors. The robot can take on different shares of each (e.g., determined by a workload-sharing parameter). The parametrization of the basic controllers and the respective shares describe the desired role of the robot. Only the physical control signals (solid lines in the control framework) are considered in the figure. The other signals (intentions, information) are neglected for the sake of clarity.

Fig. 6.1, the output is the robot's individual action plan which is executed by the action generation subsystem and applied at the interaction point with the manipulated object.

The following internal structure is proposed: Several interaction control strategies are in parallel where only one is active at the same time. The active instance is determined by the intended interaction strategy. This is indicated by the switch in Fig. 6.1. Thus, each interaction strategy determines the structure of an interaction controller. Approaches to switch between different strategies/controllers are presented by, e.g., Tsumugiwa et al. [193], Wojtara et al. [216].

Within each interaction control strategy, different robot control behaviors are defined in form of arbitrary, feedback as well as feedforward, control laws, again connected in parallel. The robot's share of each control behavior is determined first. Then, the fractions of the different basic controllers are fused. This fusion is not necessarily, but typically, realized as a summation [40, 90]. Hence, the robot's individual, planned action is defined as a weighted combination of the basic controllers. The resulting behavior is the role the robot takes on in the interaction with its partner. Thereby, control of task execution and interaction is addressed in the definition of the control laws of the different behaviors. The parameters

of all basic controllers forming the interaction controller are generally adaptive and may be adjusted based on information obtained from the environment, the knowledge base or the intention negotiation subsystem.

In the simplest case, the interaction controller consists of one interaction strategy, which, again, consists of one basic controller. This version of the proposed controller structure represents most of the assistance literature, cf., e.g., [107, 181] where the robot's share of the basic controller is determined by a workload sharing or assistance level parameter. Two different control behaviors within one interaction strategy are realized by, e.g., Evrard and Kheddar [40], Wang et al. [209] where it is either switched between the basic controllers [209] (the share is either 0 or 1) or their outputs are fused by summing them [40].

Another approach to define the internal structure of an interaction control strategy by two interaction behaviors is the independent control of internal and external forces, cf. section 2.3.2 and section 4.3.2. The external-force controller aims at influencing the object motion which directly relates to task execution, and the internal-force controller to control the internal force representing the interaction behavior between the partners.

Beside enabling the systematic design of new control strategies and the integration of existing ones, this approach puts behavioral concepts, like interaction strategy or role, in direct relation to control for the first time. This demonstrates how a **common ground for interdisciplinary work** is set up by this dissertation.

A Experimental setup

This appendix describes further details about the experimental setups used in chapters 4 and 5 of this thesis.

The experimental setup consists of two 1-dof linear haptic interfaces (designed at the Institute of Automatic Control Engineering). Each is equipped with force sensors (burstertension-pressure load cell 8524-E), wooden hand knobs and linear actuators (Copley Controls Corp., Thrusttube, motor type 2504) as shown in Fig. A.1. These haptic interfaces are characterized by their high rigidity and force capability. Measurement data is sampled with a frequency of 1 kHz . This setup allows not only the measurement of the resulting force $f_o = f_1 + f_2$ but also of the individual forces f_1 and f_2 applied by the participants.

The control of the linear haptic interfaces is implemented in Matlab[®]/Simulink[®] and executed on the Linux Real-Time Application Interface (RTAI). The graphical representation of the path runs on another computer, and communication is realized by a UDP connection in a local area network.

The control is designed to model the mechanical properties of the virtual object and the resulting rigid virtual connection between the interacting partners. Indefinite stiffness and no friction is assumed for the virtual object. Thus, the dynamics of the virtual object can be modeled according to Newton's law¹

$$f_o(t) = f_1(t) + f_2(t) = m_o \ddot{x}_o(t) \quad (\text{A.1})$$

where f_o is the sum of the forces applied by the participant/s, m_o is the virtual mass and \ddot{x}_o is the desired acceleration of the virtual object and, hence, of the linear haptic interfaces. The corresponding transfer function of the virtual model in Laplace domain

$$G_o(s) = \frac{X_o(s)}{F_o(s)} = \frac{1}{m_o s^2} \quad (\text{A.2})$$

is realized by a position-based admittance control as illustrated in Fig. A.2. Due to the high-gain inner PD position control loop it can be further assumed

$$x_o(t) = x_1(t) = x_2(t). \quad (\text{A.3})$$

Here, the physical coupling between an interacting couple is not directly via a real-world physical link, e.g., a real joint object. It is mediated by a haptic interace device. The

¹For a definition of the variables and coordinate system please refer to section 2.2.

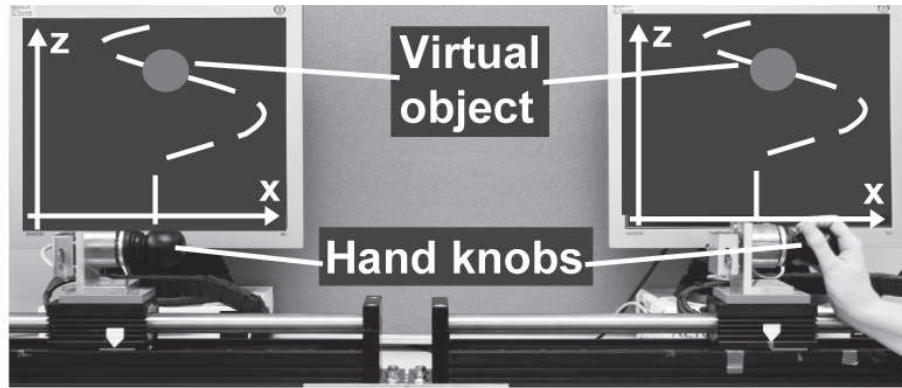


Fig. A.1: Experimental setup consisting of two linear haptic interfaces (linked by the virtual object) and two screens with the graphical representation of the tracking path; the reference path is dashed because it is visible to the participants only at the current z-position of the virtual object, ©2009 IEEE.

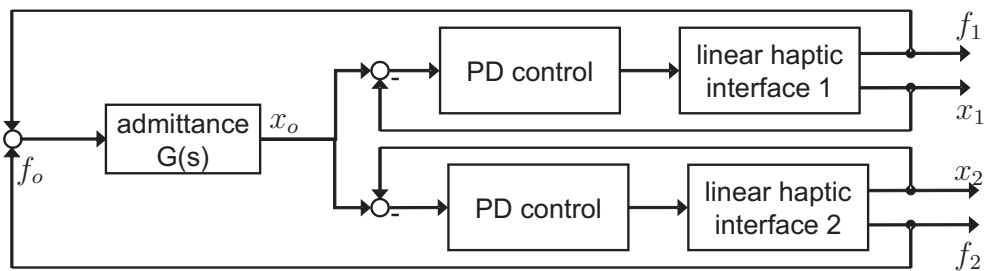


Fig. A.2: Position-based admittance control of the linear haptic interfaces used in the experimental setup enabling dyadic, haptic interaction, ©2009 IEEE

object dynamics are virtually rendered. In this case, the physical properties of the technical systems mediating the haptic interaction have to be usually considered in the derivation of its physical model. However, because of the high-gain position control running on the haptic interfaces, friction can be neglected, and the rigid object is rendered in good approximation.

B Review of Thurstone's law of comparative judgment, case 5

For each pairwise human-likeness comparison a proportion $p(S_A > S_B) = \frac{n_A}{n}$ of the number of answers n_A in favor of partner A contrasting B is received and a proportion $p(S_B > S_A) = \frac{n_B}{n}$ of answers n_B in favor of partner B contrasting A. Thereby, n is the number of pairwise comparisons AB and $p(S_A > S_B) = 1 - p(S_B > S_A)$.

The resulting proportions are summarized in the matrix \mathbf{P} with the following entries (row dominates column)

$$p_{ij} = p(S_i > S_j) \quad (\text{B.1})$$

where S_i and S_j are two presented experimental interaction partners.

Thurstone [55, 186] states that these proportions allow inferences on how clearly two interaction partners are discriminable and, hence, how distant they are on the latent scale of human-likeness. For example, interaction partners A and B will be considered more similar, thus closer on the scale, if A is perceived more human-like in only 55% of cases than in 90% of the cases. The distance between two stimuli and, hence, the difference between the respective proportions, represents their position on the human-likeness scale.

If the difference $p_{AB} - p_{BA}$ is positive, A is more human-like than B. When the frequency distribution of all these differences for the comparison AB is plotted, the true difference to be represented by the modal value of this distribution (thus, the most common perceived difference) is expected.

The area below the frequency distribution of the perceived differences represents the total number of judgments. At the zero-point of the difference scale this area is separated into two parts: one representing the cases where A is judged better than B and the other representing the cases in favor of B. Based on a normal-distribution assumption, these two areas are presented by z-values, which are related to the stimuli by

$$z_{ij} = \frac{0 - (\mu_i - \mu_j)}{\sigma_{S_i - S_j}} = \frac{\mu_j - \mu_i}{\sigma_{S_i - S_j}} \quad (\text{B.2})$$

where μ_i, μ_j are the means of the stimuli distributions.

The standard deviation of the difference distribution

$$\sigma_{S_i - S_j} = \sqrt{\sigma_{S_i}^2 + \sigma_{S_j}^2 + 2r_{S_i - S_j} \sigma_{S_i} \sigma_{S_j}} \quad (\text{B.3})$$

is a function of the standard deviations of separate observations of the two stimuli σ_{S_i} , σ_{S_j} and their correlation r . The individual standard deviations can be set to any value, as they influence only the measure unit of the human-likeness scale, which is arbitrary. Thus, $\sigma_{S_i} = \sigma_{S_j} = 1$. Furthermore, in case 5 of Thurstone's law the assumption is made that the stimuli S_i and S_j are independent. Hence, $r = 0$. This leads to $\sigma_{S_i - S_j} = \sqrt{2}$, and, hence, equation B.2 simplifies to

$$z_{ij} = \frac{\mu_j - \mu_i}{\sqrt{2}}. \quad (\text{B.4})$$

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