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Haptic Human-Robot Collaboration: How to Learn from Human Dyads

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If man made himself the first object of study, he would see how incapable he is in going further.
How can a part know the whole?
(Blaise Pascal)

To my friends and colleagues Daniela, Georg, Jan, Klaas, Markus, Thomas, and Ulrich.
This work would have been impossible without your encouragement.

Foreword

First, I would like to thank my supervisor Martin Buss for his approval of interdisciplinary work, for a great work environment, and for the freedom he admitted me specifying my research topic. Additional thanks are given to Alois Knoll and Herman Müller for providing their perspectives on this dissertation while reviewing it.

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Raphaela Groten

Abstract

When robots leave industrial settings to enter collaborations with humans in applications as rehabilitation, elderly care and entertainment, the haptic modality plays an important role in guidance and object manipulation. When working with a human user, robots should be enabled to contribute with their increasing capabilities to the shared task goal. Consequently, the robot is no longer seen as a tool, but a partner. Communication between the two partners (human and robot) via the haptic channel becomes a prerequisite. In order to allow an intuitive use, the robot should show human-like characteristics in its behavioral patterns. So far, corresponding design guidelines for robotic partners in this context are rare. The dissertation addresses this lack of knowledge by following a systematic approach based on investigations of human dyad's behavior in haptic collaboration tasks. Four achievements towards this goal are presented. First, in order to provide a profound theoretical background, a conceptual, control-theoretically inspired framework for haptic collaboration between two partners is developed. The framework describes human dyads as a reference for human-robot collaboration. Further, based on an overview of existing psychological studies as well as new experimental methods and according measurements, design guidelines for robotic partners are provided in relation to two central concerns: A) For the first time, it is shown that haptic communication exists, and that this form of feedback actually enables the integration and negotiation of individual intentions of human partners. Thus, a strong motivation for the integration of this modality in a human-like manner in control architectures is given. B) Focusing on dominance behavior, detailed guidelines for robotic behavior in haptic collaboration are derived: the dominance behavior executed by human partners in a haptic collaboration task is quantified, the changes in individual dominance behavior depending on different partners are investigated, and prediction of dominance behavior in shared decision making is enabled. The final contribution is realized by the impact on future research in the field of haptic human-robot collaboration: The experimental approach to learn from human dyads can be used as reference for further studies. The generic concept behind the framework offers a foundation for modeling robotic partners, including the results presented here.

Zusammenfassung

Wenn Roboter nicht nur im industriellen Kontext eingesetzt werden, sondern mit Menschen in Anwendungen wie Rehabilitation, Unterstützung für ältere Personen oder Unterhaltung zusammen arbeiten, spielt die haptische Modalität eine große Rolle in der Bewegungsführung und Objektmanipulation. Wenn Roboter mit Menschen zusammenarbeiten (kollaborieren), sollten sie ihre zunehmenden Fähigkeiten zur Erreichung des Aufgabenziels einbringen können. Dann ist der Roboter nicht als Werkzeug zu betrachten sondern als Partner. Die Kommunikation zwischen den Partnern (Mensch und Roboter) über den haptischen Kanal wird eine Grundvorrausetzung. Um eine intuitive Handhabung zu gewährleisten, sollte der Roboter menschenähnliche Charakteristiken in seinen Verhaltensweisen zeigen. Allerdings sind entsprechende Design-Richtlinien für Roboter in diesem Kontext kaum bekannt. Die vorliegende Dissertation adressiert diese Wissenslücke, indem eine systematische Vorgehensweise gewählt wird, welche die Untersuchung des Verhaltens menschlicher Partner in haptischen Kollaborationsaufgaben beinhaltet. Vier Erfolge hinsichtlich dieses Ziels können verzeichnet werden. Zum einen ist ein konzeptionelles, regelungstechnisch inspiriertes Rahmenwerk entwickelt worden, um den entsprechenden theoretischen Hintergrund zu bilden. Das Rahmenwerk beschreibt menschliche Partner als Referenz für Mensch-Roboter-Kollaboration. Basierend auf einem Überblick bisheriger Studien, neuen Experimenten und den dazugehörigen Messgrößen, können Richtlinien für Roboter gegeben werden, die zwei zentrale Anliegen adressieren: A) Zum ersten Mal kann gezeigt werden, dass haptische Kommunikation existiert und dass diese Form des Feedbacks daher die Verhandlung von Intentionen erlaubt. Somit ist eine starke Motivation gegeben, diese Modalität in menschenähnlicher Form in Regelungs-Architekturen von Robotern einzubringen. B) Das Dominanzverhalten in den Vordergrund stellend, können weitere Richtlinien für Roboter aufgezeigt werden: das Intervall von Dominanzunterschieden, dass zwischen menschlichen Partnern gefunden werden kann, ist benannt worden; die notwendige Veränderung in Dominanzverhalten in Abhängigkeidiet von verschiedenen Partnern ist quantifiziert worden und das Dominanzverhalten in gemeinsamen Entscheidungen konnte prediziert werden. Der letzte Beitrag dieser Dissertation richtet sich an zukünftige Forschung in Mensch-Roboter Kollaboration: Der experimentelle Ansatz von menschlichen Partnern zu lernen, kann als Referenz für spätere Studien dienen. Das generische Konzept des Rahmenwerks bietet eine Grundlage für zukünftige Modelle von Robotern, unter anderem auf Basis der hier präsentierten Ergebnissen.

Contents

Notations

Abbreviations

ANOVA	analysis of variance
CD	cognitive dominance
DoF	degrees of freedom
ds	descriptive statistics
DS	decision situation
DT	decision type
FB	feedback
HHC	human-human collaboration
HHI	human-human interaction
HRC	human-robot collaboration
HRHI	robot-mediated human-human interaction
HRI	human-robot interaction
is	inference statistics
RI	research interest
std. dev.	standard deviation
std. p.	standardized partner
VR	virtual reality

Experimental Conditions

AH	task executed **A**lone with **H**alved mass
AF	task executed **A**lone with **F**ull mass
V	dyadic task executed, only **V**isual feedback from partner
VH	dyadic task executed, **V**isual and **H**aptic feedback from partner
A, B, C	shared decision situations with increasing inconsistency in individual preferences
P1-S	partner 1 **S**hould dominate decision situation
P1-SN	partner 1 **S**hould **N**ot dominate decision situation
P1-C	partner 1 **C**an dominate decision situation

Symbols

General

fcn	function
G(s)	transfer function
i	continuous index
j	trial or interaction sequence index
k	discrete index
k_p	p-value in control of linear devices
k_d	d-value in control of linear devices
m	inertial mass of an object
N	number of samples in the task length examined
s	Laplace operator
sgn	sign
t	time index
TOL	tolerance value
$\dot{x}_o, \ddot{x}_o$	equivalent to $\frac{d}{dt}x_o$ and $\frac{d^2}{dt^2}x_o$

Force and Motion related Measures

e_1	error between descried and actual trajectory perceived by partner 1
E	energy
f_1^d	desired force by partner 12
f_1	actual force applied by partner 1
$\hat{f}_1$	estimated force applied by partner 1
f_1	force applied by partner 1
f^I	interaction force
f^E	external force
f_{sum}	summed forces of both partners
f_{diff}	difference forces as defined in Reed et al. [2005]
MAF	mean absolute force
MAF^E	movement effort based on mean absolute external forces
MAF^I	interaction effort based on mean absolute interaction forces
MAF^T	total effort based on mean absolute forces
MAP	mean absolute power
P	power
v	velocity
$w_1^1 x_{o,1}^1 ... w_1^n x_{o,1}^n$	weighted possible object trajectories (1...n) considered by partner 1
x	position
x_o	actual object position
$x_{o,1}$	object position perceived by partner 1
$x_{o,1}^d$	object position desired by partner 1

Further Measures

α	dominance parameter in state of the art
CD	continuous cognitive dominance measure
CD^b	simplified cognitive dominance measure
PD	physical dominance measure
π	qualitative context information
B	performance (measurement not specified)
$Z(B)$	*z*-standardized performance
Γ	physical effort (measurement not specified)
$Z(\Gamma)$	*z*-standardized effort
Λ	efficiency
Λ^I	interactive efficiency
Λ^E	external efficiency
Λ^T	total efficiency
RMS	root mean square error
RMS_{max}	maximal RMS found in the given sample
OT	boolean expression whether object is on target
TOT	time on target
TTC	time to task completion

Subscripts

The following subscripts can specify the below reported measures, where $(\cdot)$ can be any of the mentioned variables.

$(\cdot)_1$	partner 1
$(\cdot)_2$	partner 2
$(\cdot)_{12}$	partner 1 on partner 2
$(\cdot)_{21}$	partner 2 on partner 1
$(\cdot)_i$	individual level
$(\cdot)_d$	dyadic level

Statistics

$F_{a,b}$	value of F-statistic; a,b: DoF of variance components
p	probability of test statistic if null-hypothesis is assumed
r	correlation, if not specified further:
	Pearson correlation (can be effect size measure)
t_a	value of t-statistic; a: DoF
z	value of *z*-statistic (normal distribution)
η_p^2	partial eta square (effect size)
$P(Y)$	probability of a variable Y
μ	group mean
σ	variance
ϵ	error term
B_0 ... B_n	fixed regression coefficients
B	column matrix of regression coefficients
$\beta, \gamma, \delta, b_r$	random effects
X	predictor variable
X	matrix of fixed regression coefficients
η_{ij}	matrix of all predictors

1 Introduction

The goal of this dissertation is to outline a generic experimental approach to design guidelines for robots, which are built to collaborate with a human user in a haptic task. Despite the technical advances that enhance robots acting in dynamic, unstructured environments, their collaboration with human users is still challenging. For successful collaboration, the robot has to be enabled to contribute with its increasing capabilities to shared task execution. Such capabilities may be cognitive (e.g. accurate memory, rational decision making), or physical (e.g. strength, precision, endurance). Furthermore, the robot may need to adapt the task execution to situation-specific capabilities (e.g. workspace restrictions). Thus, in collaborative scenarios the robot should be seen as a partner with its own action plans, which need to be integrated with those of a human partner. It is claimed that the robot should show human-like behavior characteristics to offer an intuitive understanding of its actions to the human user. As Marble et al. [2004] state: "The human must be able to understand the reason for and effects of robot initiative. These requirements can only be met through careful application of human factors principles", see also Clodic et al. [2005]; Demiris [2007]; Fong et al. [2005]; Grosz [1996]; Tahboub [2004] for this line of argumentation.

So far there is little known about human behavior characteristics in haptic collaboration. To the author's best knowledge no investigations on the integration of individual action plans exist in this context. Therefore, this dissertation addresses the behavior of interacting human dyads theoretically as well as experimentally, in order to understand general principles of human haptic collaboration. Based on this systematic approach, first design guidelines for robotic partners in haptic collaboration can be derived, and a foundation for the acquisition of further guidelines is given.

In order to motivate the research interest in haptic human-robot collaboration, the following section gives application examples.

1.1 Applications of Haptic Human-Robot Collaboration

In Burghart et al. [2002] a classification of haptic collaborative tasks is presented. The goal of this classification is to reduce the complexity of haptic collaboration research by focusing on task specific aspects. Mostly, haptic collaboration research focuses on interaction between *two partners (dyads)*; however, it can take place within bigger teams as well. Following Burghart et al. [2002], two categories of haptic collaboration are distinguished in this dissertation:

1. joint object manipulation

2. haptic collaboration without object

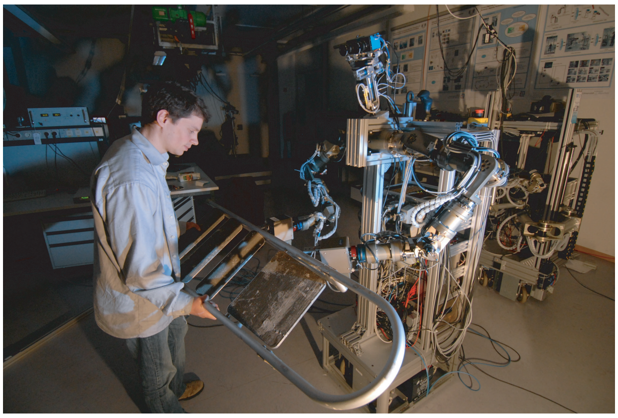


Figure 1.1: Example of a human collaboratively carrying an object with a robot.

Within the first category the task may require the partners to jointly *place* / *remove* or *carry* the object [1]. These actions can be further specified e.g. by environmental constraints, goal positions, and object characteristics. Whether a partner is actually necessary for successful task execution depends on these task-related attributes (compare e.g. Richardson et al. [2007]). An example of a haptic task in human-robot collaboration, i.e. object carrying, is given in Figure 1.1.

The second category represents tasks such as *guiding* in kinesthetic teaching scenarios (called "leading" and "restricting" in Burghart et al. [2002]), which involves assistance to handicapped people, rehabilitation or dancing. Tasks of this category are often related to dominance-, capability- or knowledge-differences between the partners. These tasks are not defined for a single person (with the possible exception of guiding one's own limbs e.g. for stroke patients).

Robots can be partners in both task categories. They can collaborate in tasks taking place in reality, or virtual reality environments (VR). Some exemplary scenarios are listed below:

- **Autonomous assistants and service robots:** Especially in the fields of elderly care, assistance for handicapped (e.g. blind) people, but also as general household assistance, robots are introduced as every-day partners, which are able to support humans in haptic tasks by collaboration. Some exemplary scenarios include a) autonomous helpers which can help to carry bulky objects such as a fridge or a table, see Kosuge and Hirata [2004]; b) an interactive shopping trolley as developed by G?ller et al. [2009]; c) a wheelchair which vision-based cognitive system controls the movement direction collaboratively with the human, see Carlson and Demiris [2008]; d) an intelligent walker, which adapts break torque to the human and the environment presented by Hirata et al. [2005a]; e) a walker for blind people e.g. Lacey and Rodriguez-Losada [2008].

- **Entertainment:** Virtual reality (VR) scenarios are often unrealistic without haptic feedback (when users can reach through objects without feeling restrictions), especially in social interaction with partners (e.g. handshake scenario in Wang et al. [2009]). In addition, robotic partners are introduced in real life entertainment such as in dancing, see e.g. Takeda et al. [2007a].

- **Medical training:** In order to teach high-level motor skills as required in medical applications, haptic collaboration is employed to enhance the skill transfer between humans as

[1] It has to be mentioned that objects can be transformed without moving them, however, this is not considered here.

e.g. in Esen et al. [2007]; Nudehi et al. [2005], or between a virtual agent and a human trainee, e.g. Bettini et al. [2004]; Kragic et al. [2005].

- **Rehabilitation and Therapy:** The importance of haptic feedback in physical rehabilitation has been stressed e.g. by Broeren et al. [2006]; Choi et al. [2010]; Fan et al. [2009]; Popescu et al. [2000]. So far robots have been used in the therapy of autistic children with kinesthetic tasks [Robins et al., 2009]. However, the two partners (child and robot) were not physically connected. In Morasso et al. [2007] the importance for haptic feedback in therapy is outlined.

- **Telepresence:** Signal-exchange between one or more humans and a remote environment is challenging. The development of assistance functions allows more accurate task execution for two human operators acting in the same remote environment, or when the performance of an individual operator is enhanced by assistance provided by a virtual agent. This is of high relevance in situations requiring precise manipulations as in outer space, compare e.g. Hirzinger et al. [2005]; Oda et al. [2001].

- **Vehicle / aircraft control:** In a first experiment Griffiths and Gillespie [2005] outlined the benefits of partly autonomous steering-wheels when keeping a virtual car on the lane, avoiding obstacles. Another study investigating the effect of haptic guidance in curve navigation while driving was conducted by Mulder et al. [2008]. Furthermore, Field and Harris [1998] compared different cross-cockpit linkages for commercial aircrafts.

It has to be mentioned that the precise separation between the classification of a robotic partner and an assistance function is still subject to discussion. Here, an assistance function is considered less autonomous than a robotic partner. Thus, the last two categories are listed as possible fields of application. There, however, the focus is on assistance functions, as the scenarios generally require the responsibility for the task execution to be on the human side.

1.2 Open Challenges

If the goal is to design a robotic partner, which is able to collaborate in haptic tasks, in contrast to a tool operated by the human user, behavior guidelines for the robot have to be established. On the one hand the robot has to act in a way, which enables an intuitive collaboration for the user; on the other hand it has to understand and adapt to the user's actions. Therefore, one main challenge in this field of research is to determine rules, which describe human behavior in haptic tasks in order to provide the robotic partner with an appropriate model of the human user and to derive guidelines for the robot itself.

In order to approach this goal ways have to be found to scientifically investigate human behavior. This can be done by psychological experiments. However, limited knowledge exists on the *methodology of psychological experiments* in the context of haptic human-robot collaboration. This leads to two phenomena: First, general guidelines on how to design experiments in this context are rare. Second, this lack of pre-knowledge results in rather unsystematically related research interests. Consequently, it is challenging to relate existing results to each other as no *integrating conceptual framework* is established so far.

In the author's opinion one central challenge, which should be addressed in a first step, is an empirical proof of the *existence of haptic communication*. If human dyads do not communicate via this channel, in the sense of goal-oriented *integration of individual action plans*[2], there is no point in building robots, which relate to this behavior. If haptic communication exists, further research effort on the engineering side to overcome challenges related to instabilities due to bilateral energy exchange in direct contact can be considered worthwhile. In addition, psychological studies on human behavior can only be motivated by positive effects of haptic feedback between partners. Then, psychological experiments should focus on potential key-factors in haptic collaboration. Fundamental knowledge of haptic collaboration so-gained is required to support dynamic modeling as a prerequisite for building robotic partners in this context.

1.3 Definition of Haptic Collaboration & Main Assumption

There is no clear agreement on the definition of haptic collaboration in literature. Therefore, this section will provide a working definition. Accompanying definitions can be found in Appendix A.

This thesis investigates collaboration based on the *kinesthetic* part of the **haptic** sense in contrast to tactile information (though, the general term "haptic" is used in the following). "The kinesthetic system receives sensory input from mechanoreceptors located within the body's muscles, tendons, and joints" [Klatzky and Lederman, 2002]. Haptic perception always involves the exchange of (mechanical) energy - and therefore information - between the body and the world outside [Hayward and Astley, 1996]. The most important characteristic of this sense is that it is the only human sense, which is capable of perception *and* additionally directly related to action: the human motor system. Hence, the haptic information channel is interactive per se, as it allows us to sense *and* act on our environment. It is agreed with Hayward and Astley [1996] that the resulting "bidirectionality is the most prominent characteristic of the haptic channel". This is the reason why literature sometimes refers to "haptic interaction" in scenarios where *one* person manipulates an object. However, throughout this thesis this term is reserved for interaction between two cognitive systems, independent whether it is a human dyad or a human-robot team.

If two partners want to accomplish a task together, they do not only **interact** but **collaborate**. "Whereas interaction entails action on someone or something else, collaboration is inherently working *with* others" [Hoffman and Breazeal, 2004], referring to [Bratman, 1992; J.Grosz and C., 1990]. Collaboration requires sharing task goals. This implies the recognition of the partner's **intentions** (= action plans towards a goal) and the integration into one's own intentions, i.e. the **negotiation** of shared intentions in case of different individual intentions. Shared intentions "are not reducible to mere summation of individual intentions" [Kanno et al., 2003]. Hence, when two systems collaborate, the partners share at least one goal (what) and are confronted with the challenge to find suitable action plans (how) to achieve it [Grosz, 1996; Johannsen and Averbukh, 1993; Tomasello et al., 2005].

Haptic collaboration is based on the exchange of *force and motion signals* between partners, either in direct contact (e.g. the hands in guidance) or via an object which is jointly manipulated.

[2]this will be defined more explicitly as "intention negotiatio" in the next subchapter

As long as there is physical contact between the two partners the physical coupling leads to a constant signal flow between partners. Thus, haptic collaboration is *simultaneous and continuous* because the partner's dynamics are perceived while acting. This direct feedback is the main difference to turn-taking in talking and to forms of collaboration, where cooperation takes place mostly sequentially, see e.g. Meulenbroek et al. [2007]; Schub? et al. [2007]; Sebanz et al. [2003a]; Welsh [2009]. Not all signals transferred between partners are assumed to have a symbolic character, i.e. are meant to transport individual intentions to the partner (compare Frith [2008]). Therefore, one challenge in haptic collaboration research is to find out if and how partners communicate via signals, and how shared action plans look like. Herein, *mutual* haptic feedback is a key-concept. Precisely, "mutual" refers to the fact that both partners are able to perceive and act upon each other via this signal exchange allowing adaptation processes, which is a prerequisite for collaboration, i.e. shared action plans.

The **main assumption** of this dissertation is that most tasks, which require haptic collaboration, can be described on an abstract level as the execution of a shared trajectory. This can be the trajectory towards a goal position in joint object manipulation, or a guidance scenario. Furthermore, the goal may lie in the actual following of the trajectory as e.g. in dancing. Thus, when two partners collaborate in a haptic task, they have to find a task-optimal trajectory for this interaction point or the object. This implies that the shared action plan towards a task goal in haptic collaboration can be based on the negotiation of trajectories between partners, compare also Evrard and Kheddar [2009] for this consideration. Thus, haptic collaboration is closely linked to manual motor control tasks. The partners can exchange forces to push or pull in different directions and, by doing so, influence the partner and the shared trajectory. Depending on the agreement between the partners on the shared trajectory these forces may vary, reflecting the different intentions of the partners.

In addition to one's own proprioceptive feedback, haptic feedback from the partner and the jointly manipulated object, feedback from other modalities is also involved in most haptic collaboration scenarios: usually the partners can visually perceive the environmental changes which are caused by their haptic interaction, and may also use verbal communication. However, throughout this dissertation verbal communication is neglected in favor of a clear focus.

1.4 Approach

Two different approaches to investigate haptic collaboration between humans and robots can be separated:

1. Studying two interacting humans with the goal of knowledge-acquisition on intuitive haptic collaboration. Then, a model for one human within the dyad can be developed for the implementation on a technical partner - one human is "substituted" by the robot. Afterwards, the model can be transformed for an increased use of the individual capabilities of the specific partners without loosing the human-like collaboration patterns. This approach is located early in the design process as it defines requirements of robots *before* they are developed.

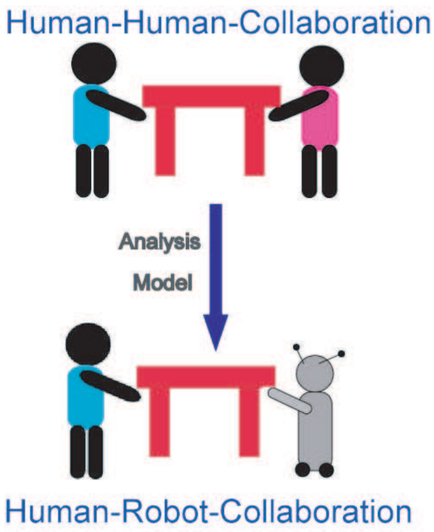


Figure 1.2: The chosen approach in this dissertation to design intuitive technical partners for haptic collaboration tasks is to analyze and model two collaborating human partners (*HHC*) in controlled experiments in a first step. Then, one human is "substituted" by a robot on the basis of these models. Thus, the knowledge from HHC can enhance human-robot-collaboration (*HRC*) in actual applications.

2. Investigating directly how humans collaborate with robots by evaluating the human-robot interaction depending on variations in specific parameters. This, however, requires an existing model of an interacting partner. Thus, the approach can be chosen *later* in the design process of robotic partners when pre-knowledge exists, which allowes for a first prototype of a technical partner.

Both approaches should be combined when building technical partners. Starting with the first approach is useful for information on key-concepts and influencing factors which leads to the development of a model. Once this model or a simplified form is implemented on a robot, it needs to be evaluated. For the successful introduction of a robotic partner for haptic collaboration tasks, this process will be run through iteratively.

At the moment few models are available, which can be implemented on technical partners for haptic collaboration. Thus, recent research in this field relies on human-human haptic collaboration (HHC) as a reference when designing technical partners i.e. follows the first approach [Corteville et al., 2007; Evrard and Kheddar, 2009; Rahman et al., 2002a; Reed et al., 2006]. It is argued by these authors that intuitive human-robot collaboration (HRC) has to be based on rules and models familiar to humans. In Hinds et al. [2004] it is put forward that humans "will be more at ease collaborating with human-like robots", because they "may be perceived as more predictable" and "human-like characteristics are likely to engender a more human mental model of the robot", when estimating its capabilities. The argument is supported by Wolpert et al. [2003], where it is stated that if no other mental model is available, we tend to use the mental model of ourselves for the partner. Therefore, this dissertation is an attempt to understand human-like haptic collaboration behavior by studying human dyads. The gained knowledge can then be transfered to human-robot collaboration (substitution approach), compare Figure 1.2.

Note, that this human-likeness is not interpreted as a replay of human behavior but a deeper understanding of key-concepts.

Independent of the approach, at least one human partner is involved in the corresponding studies. As an implication for haptic collaboration research **psychological experiments** are required: Due to the generally high variety and complexity of human behavior, a high quality of experimental design and analysis is necessary in order to enable causal inferences, taking into account the variability in human behavior and still allowing for statements on a general level representing the population of potential human partners.

Thus, this thesis will present psychological experiments on collaborating humans to understand key concepts in haptic collaboration and derive guidelines for the development of robotic partners resembling the first approach.

1.5 Main Contributions and Outline

In order to address the challenges in the research field of haptic collaboration between humans and robots, this thesis attempts to systematically investigate haptic collaboration between two human partners as a reference for haptic human-robot collaboration. Within a stepwise approach, the following main contributions can be separated:

1. development of a conceptual framework for haptic collaboration
2. profound introduction of experimental methods including the introduction of new experimental designs and measures in relation to state-of-the-art experiments
3. experimental investigation of the existence of “haptic communication” between humans
4. analysis of characteristics of shared actions in haptic collaboration

Based on these four steps, it is not only possible to derive first design guidelines for robotic partners in haptic collaboration, but in addition, future work can profit from the theoretical background and the presented methodologies. This potential impact on future research can be interpreted as another contribution of this dissertation.

In the following, the main contributions are summarized in more detail relating to the open challenges in this research field. At the same time, an outline of the thesis is given:

A **Conceptual Framework for Haptic Collaboration** is developed in **Chapter 2**. It serves as a basis for systematic psychological experiments and as a theoretical background for future modeling attempts. This framework is based on theoretically derived requirements on haptic collaboration partners (whether human or robot) in line with existing interaction models, which are mainly developed in the context of human-computer interaction or supervisory control. The new framework is presented thoroughly and discussed in relation to the requirements. The purpose of this work is two-fold: On the one hand, the close relation to control theory inspires future models for robotic partners and supports the substitution-approach when transferring knowledge from human dyads to human-robot collaboration. On the other hand, the framework enables the structuring and integration of experimental research in haptic collaboration by identifying

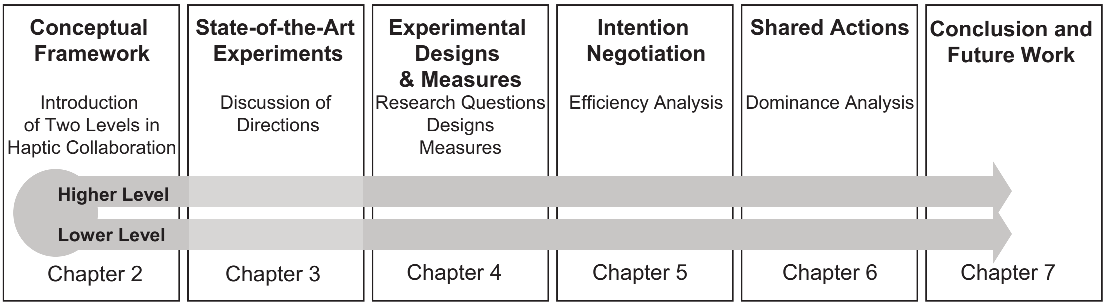


Figure 1.3: Overview on the composition of Chapters 2-7

important concepts, structures and signal flows. This way, it is possible to precisely classify which key-components are addressed in an experimental study. So far, no framework on haptic collaboration exists in literature. Within the framework two levels of haptic collaboration are distinguished depending on the processed intentions: The lower level refers to a collaboration effort which integrates the two individual force outputs task oriented. Thus, dealing with the challenge to agree on strategies on *how* to move an object. The higher level is defined by shared decision making between partners on *where* to move. These two levels structure the research presented in the remainder of the thesis, where the experimental design and related analyses distinguish between these levels, compare Figure 1.3.

Before new experiments are designed, within the conceptual framework to investigate human dyad behavior in haptic collaboration, a **Discussion on Directions in State-of-the-Art Experiments** is presented for the first time **(Chapter 3)**. This discussion is based on an overview of more than 80 studies conducted in haptic collaboration, see Appendix B. Challenges in the design of future experiments in the context of haptic collaboration are identified within this chapter.

Taking into account the conceptual framework as well as the state of the art in experimental research on haptic collaboration, new experiments are designed (**Chapter 4**), separating **Experimental Designs and Measures**: First, two general research questions are elaborated, which are addressed by the experiments presented in this thesis. Then, two new psychological experimental designs, investigating behavior on the two haptic collaboration levels, are introduced. In the next step, measurements to analyze the behavioral data gained by the experiments are derived. The experiments and measures are the basis for the results obtained in the following chapters. Additionally, the choice of experiments and measures is motivated extensively to show the general relevance in the research field beyond the results presented here. To the author's best knowledge neither the experimental design nor the measures have been used in any other studies on haptic collaboration than those presented here.

Experimental results are presented in relation to the theoretical considerations and experiments designed in the previous chapters. The analyses address the two central research questions: 1) Does haptic communication exist? **Intention Negotiation** between human partners via mutual haptic feedback is investigated in **Chapter 5** employing an efficiency measure; 2) How do **Shared Actions** in haptic collaboration look like? As one important concept, dominance in human dyad behavior is addressed as a measure of individual responsibility for the shared actions (**Chapter 6**). Within both chapters human behavior is analyzed separately for the two levels of haptic collaboration. Thus, shared decision making is studied for the first time in haptic collaboration. On the basis of the derived results, **Design Guidelines** for robotic partners in haptic collaboration are identified.

The last chapter draws general **Conclusions** and gives an outlook on future research in haptic collaboration (**Chapter 7**). The provided theoretical knowledge in the conceptual framework, the results on intention negotiation and shared actions, the experimentally derived design guidelines, as well as the recorded data, which allow further analyses, go beyond the work presented here, and are promising tools for an enhancement of robotic partners in the future.

2 Conceptual Framework for Haptic Collaboration

This thesis aims to broaden the understanding of human behavior in jointly executed haptic tasks in favor of more intuitive human-robot collaboration. This is approached by addressing the behavior of human dyads as a reference. Thus, the goal within this field of research is a systematic investigation of human collaborative behavior. Theoretical knowledge on internal processes leading to this behavior is required as a first attempt to structure the corresponding experiments and to enhance modeling of robotic partners in this context.

Even though interaction models describing information processes in man-machine interaction exist, they mainly focus on human-computer interaction or supervisory control. The first group of these models does not take components specific to haptic collaboration into account, the second group of models does not describe the behavior of two collaborating partners, but how humans control non-autonomous systems. In [Kanno et al., 2003] (referring to [Hutchins, 1996; Paris et al., 2001]), it is stated that "the basic function of man-machine interfaces is limited to information exchange lacking more conceptual and intentional aspects of communication that enable humans to manage cooperative work efficiently". Therefore, the focus of a framework that describes internal processes of partners collaborating via haptic signals should be on intentional components including adaptation towards the partner. In order to allow real collaboration, the integration of individual intentions of two cognitive systems is required. To the best of the author's knowledge, so far no framework exists, which describes such processes responsible for the resulting behavior in a collaborative haptic task.

The following chapter introduces a conceptual framework [1] of haptic collaboration based on the requirements identified by discussing existing interaction models and their relation to haptic collaboration. The framework enables structuring of future studies on haptic collaboration and (control-theoretic as well as statistic) modeling in general and specifically for the work presented in the following chapters: Referring to the framework, it is possible to determine which components are experimentally addressed or modeled, leading to a higher quality in integration of and comparisons between corresponding results. The close relationship of the haptic collaboration framework introduced to control-theoretic modeling encourages the knowledge transfer between experimentally gained design guidelines from human-human collaboration and the actual modeling of robots.

Requirements of a framework for haptic collaboration are identified in Section 2.1. Then, the framework itself is described in Subchapter 2.2. In Subchapter 2.3 the framework is discussed in relation to the requirements. Possible extensions and implications for experimental research and

[1] Note that the haptic collaboration framework is called "framework" in contrast to "model" because it consists of a broad structure focusing on generalizability, rather than on precise predictions expected from a model. Hence, parameters and signal flows are not described in enough detail to talk about a model. However, guidelines for models are implicit to the framework. If the authors of cited papers referred to their work as a "model" the term is repeated here.

Figure 2.1: Simple model of human information processing [Parasuraman et al., 2000]

robotic partners are outlined. The chapter ends with a conclusion including an outlook on future work.

2.1 Requirements and Related Work

The author agrees with Johannsen and Averbukh [1993] that recent developments in human-robot interaction demand "more comprehensive modeling of human performance than it was necessary for traditional supervisory and control systems". When there is haptic collaboration with robots, the human does not control a system with abstract inputs in a supervisory manner anymore. Instead, the human is part of the overall system and should be allowed to interact intuitively by developing shared action plans with the partner. To understand this process, two humans are considered within the framework. Later research will have to find ways to design robots accordingly to substitute one partner. Focus of the framework is to provide means in order to achieve this goal. Next, necessary components for a haptic collaboration framework are investigated by relating to literature on interaction models.

2.1.1 Feedback Loop

In the context of human-machine interaction, Parasuraman et al. [2000] introduce a four stage model of human information processing in general (see Figure 2.1). Here, this model is considered as a starting point from where further requirements are added. First, information is registered, then consciously perceived and processed. Within cognitive processes decisions are reached, and finally an action is implemented based on these decisions. This model is introduced to specify the capabilities of a technical partner, which are related to its autonomy, separately for these stages. It emphasizes the importance of decision making, i.e. choosing an action out of several possible. In this simplified model, no feedback loops are included. Thus, the information, whether an action led to an achievement of the desired goal is not part of the model.

In an interaction model proposed by Norman [1998] it is emphasized that the chosen actions are expected to be goal-oriented. To ensure this, the evaluation of executed actions is required in relation to these desired goals. This is described as a feedback loop. In a seven level model of human task performance it is strengthened that actions are not only executed, but additionally evaluated, see Figure 2.2. In this model "interaction" refers to an exchange between the human and the environment. The model describes the development of a goal towards the "intention to act", to a sequence of actions, and the actual execution of this sequence which transforms the environment. The state of the environment is then perceived and interpreted, and finally the interpretations are evaluated. This evaluation may influence the goal. Thus, a feedback loop is introduced which can influence actions before (intermediate) results are reached, and which may

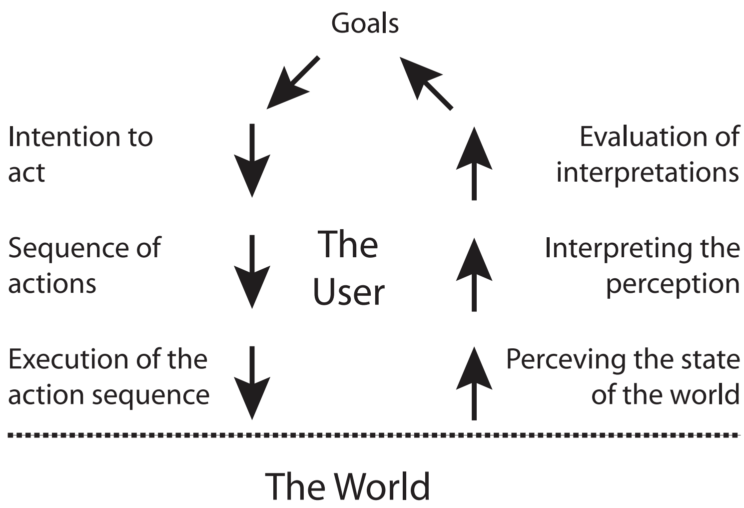


Figure 2.2: This figure illustrates the feedback loop of individual goal-oriented actions as proposed by Norman [1998]. This model is called interactive, relating to the interaction with the world. Thus, further components have to be added to use the feedback loop in a description of haptic collaboration.

lead to further goals and sub-goals.

This feedback loop, which allows an adaptation of goals, seems crucial for haptic collaboration, where two individual actions are continuously combined. It seems reasonable to assume that both partners should be represented by such feedback loops. In dependence on the perceived partner's action and the resulting changes in the shared environment, own action plans may have to be transformed to achieve the shared overall goal. The continuous feedback of the partner's actions as provided in haptic collaboration allows receiving information on the partner's actions in addition to feedback of the own actions *continuously*. This should enable negotiating or adapting intentions with/towards the partner during task execution before the final goal is reached. However, additional components are required to model the integration of two action plans. It is unclear, which information is exchanged between the two partners. As a first step, the next section considers information processed by one individual before the exchange is discussed further.

2.1.2 Levels in Information Processing

A well-known model of human performance and information processing for the design of man-machine interfaces is developed by Rasmussen [1983], who classifies different types of processed information. The model distinguishes between familiar and unfamiliar tasks and resulting cognitive demands on the human. Therefore, it is differentiated between skill-, rule- and knowledge-based task-levels, compare Figure 2.3. The processed information is grouped in three categories: signals, signs and symbols, in relation to the task-level. According to the author the *same physical cue* is interpreted differently on each level:
1) "At the *skill-based* level the perceptual motor system acts as a multi-variate continuous control system synchronizing the physical activity in such as navigating the body through the environment and manipulating external objects in a time space domain. For this control the

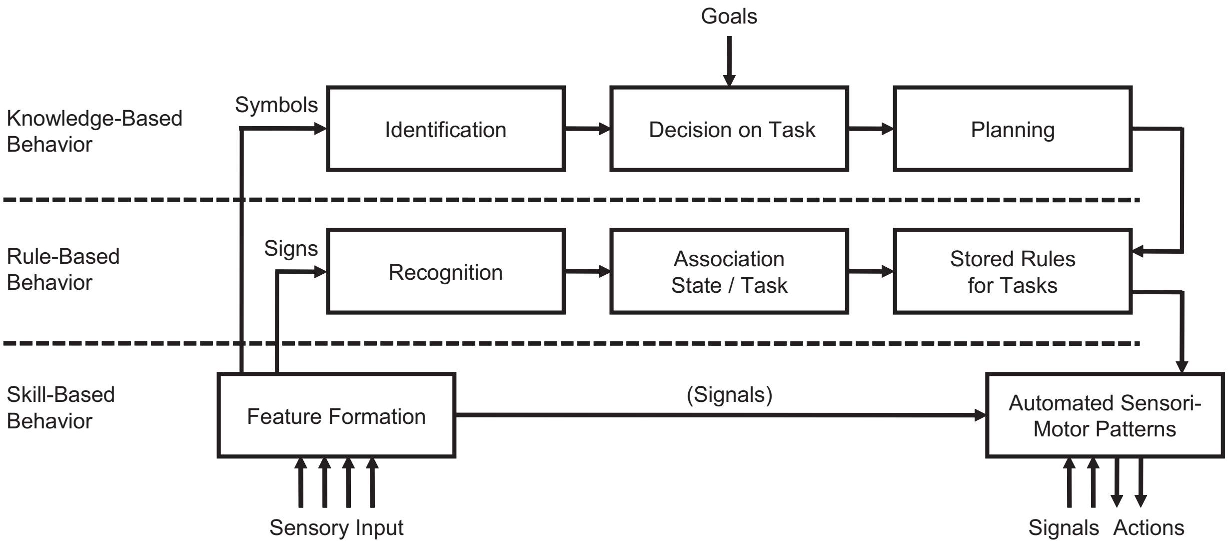


Figure 2.3: "Simplified illustration of three levels of performance of skilled human operators. Note that levels are not alternatives but interact in a way only rudimentarily represented in the diagram" Rasmussen [1983]

sensed information is perceived as time-space *signals*, continuous quantitative indicators of the time space behavior of the environment. These signals have no meaning or significance except as direct physical time space data". On this level, information is processed subconsciously, interpretation is not necessary.
2) "At the *rule-based* level, information is typically perceived as *sign*. The information perceived is defined as a sign when it serves to activate or modify predetermined actions or manipulations. Signs refer to situations or proper behavior by convention or prior experience. [...] Signs can only be used to select or modify rules controlling the sequencing of skilled subroutines". Signs can also trigger skill-based actions. This level is associated with "if-then rules" by [Wickens, 2004, Chapter 7].
3) For the *knowledge-based* level, it is stated: "To be useful for causal functional reasoning in predicting or explaining unfamiliar behavior of the environment information must be perceived as *symbols*. [...] Symbols are defined by and refer to the internal conceptual representation which is the basis for reasoning and planning." When no rules are stored analytic processing using conceptual information is necessary. Symbols relate to "goals and an action plan" [Wickens, 2004, Chapter 7].
The processing of sensory input by one or several levels leads to the execution of rule-based or automated actions. Rasmussen's model was established in the context of interface design for supervisory control. The model clearly states that one sensory input can have very different meanings. In haptic collaboration, not only physical cues from the *environment* are processed as signals, signs or symbols, but it is assumed that the physical cues caused by the partner's *behavior* are processed accordingly in haptic collaboration: his/her actions may be processed subconsciously, trigger behavior rules or may require reasoning and prediction on the underlying intentions. Thus, the introduction of this different levels of information processing seems crucial for intention recognition and resulting action plan negotiation as a main concept in haptic collaboration. How negotiation of intentions between partners based on the different levels of

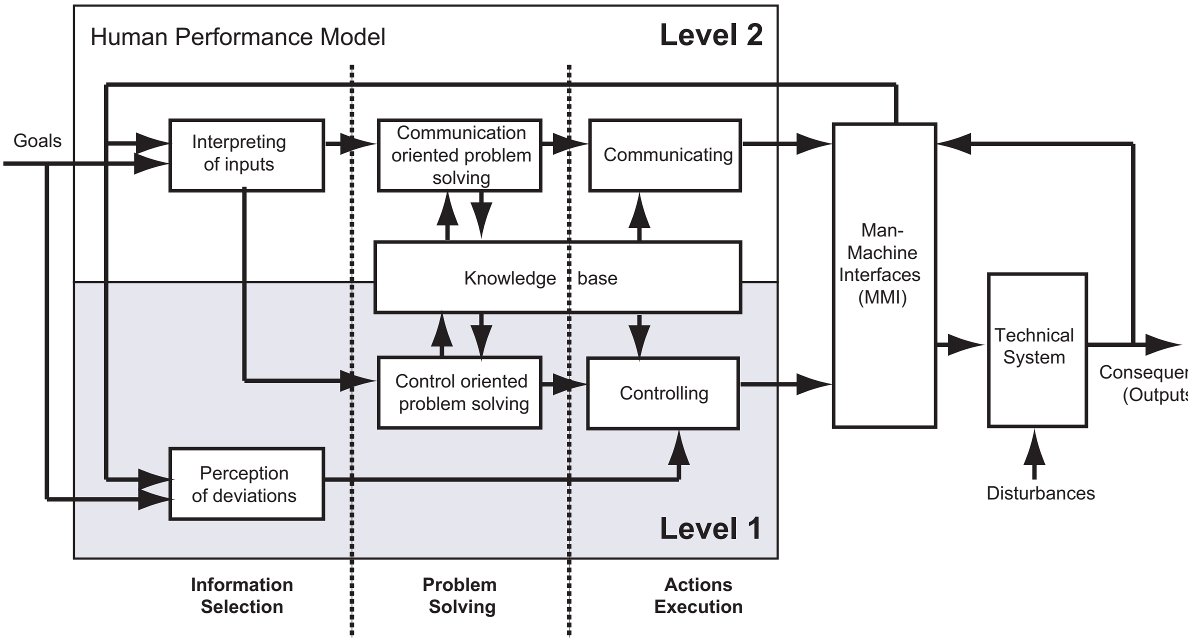


Figure 2.4: This figure describes a performance model for human-machine interaction described in Johannsen and Averbukh [1993]. A supervisory (1) and a communicative (2) level are differentiated, resulting in different channels of interaction with the interface. Both levels refer to a knowledge base.

information can take place has to be specified further.

One model which also differentiates levels of processed information is proposed by Johannsen and Averbukh [1993]. Only two levels are distinguished and depicted in Figure 2.4. In contrast to Rasmussen [1983] these two different levels are also separated within the communication taking place via a man-machine interface. The first level is a control function level, which is related to supervisory functions within a task. The second level is a communication-specific level. On both levels the processes of information selection, problem solving and action execution take place. Both, control and communication level exchange information with a knowledge base. The authors assume human behavior needs to be modeled for both levels. In this model, two different channels of interaction are defined in accordance with the two levels.

When transferring concepts of this model to haptic collaboration (leaving other modalities aside), it is important to clarify that only one channel transports information. Via haptic signals the object is manipulated and intention negotiation with the partner via force and motion signals takes place. Still, we can assume different levels of information processes (communicative and supervisory) internally in the partners.

Another model which addresses the fact that the information exchanged between partners can relate to different internal levels is presented by Schomaker et al. [1995]. Four observation levels of in- and outputs between two systems are distinguished:
1) *Physical layer*: describes characteristics of the device or the human
2) *Information-theoretical layer*: informs about bandwidth, data compression and other communication characteristics of the two systems

3) *Cognitive layer*: transforms representational, procedural aspects of interaction into syntax and semantics such as pattern recognition and learning. This level is the bridge between low-level and high-level (intentional) activity.
4) *Intentional layer*: processes goals, believes, and the information from lower levels
This model stresses the fact that goals are not *directly* exchanged in interaction and that the actual information which is exchanged depends on characteristics of the involved systems. Except for this necessary compatibility of the two systems to allow information exchange (and thus the recognition of exchange and negotiation of intentions), this model introduces different levels of abstraction in the context of interaction, in line with the models presented above.

It is important to note that the action goals, which are referred to in the presented models, can themselves have a hierarchical order [Carver and Scheier, 2001, Chapter 5]. An overall goal can consist of different sub-goals, which can be further distinguished into desired motor commands. Action plans therefore exist on several levels as well, as they contain the plan to achieve those goals. Thus, depending on the task, the goal of haptic collaboration can be described differently, e.g. the goal to empty a room full of certain objects collaboratively, contains the subgoals to grasp, lift, and move these objects along position trajectories. For the joint achievement of a goal, the two individual action plans need to be combined. To make this possible, the individual needs a representation of what the partner is intending. Representation is addressed in the next section.

2.1.3 Mental Models

After summarizing models with internal feedback structures and different levels of processed information and goals, the relation between this information and the environment is now addressed. This is done by introducing *mental models*, which are an internal representations of the external world, including the collaborating partner. Mental models allow to explain and predict a system state and to recognize the relationship between system components and events [Wilson and Rutherford, 1989]. Recently mental models receive increasing attention in interaction design processes [Cooper et al., 2007; Galitz, 2007; Sharp et al., 2007]. Herein, it is aimed to derive high system performance based on the approach that the user can rely on existing mental models when interacting with technical devices. In Richardson et al. [1994], the general action-perception loop is further extended by mental models and the concept of learning. Three different types of mental models are distinguished:
1) “Ends models” deal with perception and information about what one is trying to accomplish (goals)
2) “Mean models” contain plans of actions / strategies (intentions)
3) “Mean/ends models” inform on feedback structures and rules

Based on the mental models, the state of the system, which the human interacts with, is predicted and actions on this system are planned. In this context, *learning* is defined as “processes by which people change their mental models” and involves changes in: action plans (means), goals (ends), cue selection including its interpretation, and changes models of system functions (means-ends). Learning happens via the feedback loop from the outcome of our actions. In collaboration, both partners need to find *shared* mental models, to work on the basis of the same representations and to exchange information which can be interpreted correctly, see e.g.

Doyle and Ford [1998]; Klimoski and Mohammed [1994]; Levesque et al. [2001]. The concept of shared mental models is closely related to intention recognition, common ground, theory of mind and social cognition. The importance of shared mental models for man-machine interaction is stressed by e.g. Hwang et al. [2005]; Johannsen and Averbukh [1993]; Rouse and Morris [1998]; Staggers and Norcio [1993].

Shared mental models are assumed to be necessary components in an architecture modeling behavior for successful haptic collaboration. We need to know the state of the partner and integrate it into our own action plans. Therefore, this component should be part of the framework.

The computational framework established by Wolpert et al. [2003] introduces mental models to kinesthetic tasks in interaction. It deals with processes of imitation learning where two humans are not physically coupled. First, a social interaction loop is described: A motor command causes "motor consequences" in the environment which generates a communicative signal. When this is perceived by partners, it can have "influence on their hidden (mental) state which constitutes the set of parameters that determine their behavior". Therefore, "if we know the state of someone else and have a model of their behavior, we should be able to predict their response to a given input". Several challenges in this procedure are mentioned:
1) There is time delay between actions and responses in a dynamic environment, making causal inferences hard to predict.
2) Due to a generally complex, noisy, non-linear relationship between actions and consequences of one partner, the response of the other person to this partner's actions is hard to predict. Thus, there is noise in both partner's perceptions of actions and in the perception of responses.
3) Because social interaction can involve interaction with multiple partners, which have different dynamics, there exists no general model for all of them.
Motivated by these challenges, the authors assume that the internal models of the partner have to be learned: "An inverse social model could be used to try to achieve some hidden mental state, and hence behavior, in another person". Whereas for the consequences of one's own movements, easy to learn feedforward models are proposed by Wolpert et al. [2003], for the estimation of the partner's hidden states inverse models are required: from the consequences we perceive the motor command behind has to be estimated. Again some challenges have to be met: The degrees of freedom in the internal models of the partner are "enormous". Furthermore, for system identification, one would need a battery of inputs which cannot be given to a partner. It is assumed that learning of the others hidden states can take place due to the fact that the partners are similar. Thus, the framework proposed by Wolpert et al. [2003] provides further arguments in favor of human-like robotic partners, which can then be predicted easier by the human user. In agreement with models presented in the previous section, the framework from Wolpert et al. [2003] suggests a (hierarchical) structure for the control and extraction of intentions. According to the authors, this hierarchical, tree-like structure has elements of motor control on the lowest level and more abstract representations as intentions and goals on higher levels. This is in line with a statement by Frith [2008]: "the sharing must occur on many levels of representation".

In Cannon-Bowers et al. [1993], it is reasoned that a team member has multiple mental models of the task, and the team. The partners must understand the dynamics and control of the equipment (object), the task, and the environment, their role in the task and they should have

Table 2.1: Multiple Mental Models in Teams as proposed by Cannon-Bowers et al. [1993]

Type of Model	Knowledge Content	Stability of Model Content
Equipment Model	Equipment functioning Operating procedures Equipment limitations Likely failures	High
Task Model	Task procedures Likely contingencies Likely scenarios Task strategies Environmental constraints	Moderate
Team Interaction Model	Roles / responsibilities Information sources Interaction patterns Communication channels Role interdependencies	Moderate
Team Model	Teammates' knowledge Teammates' skills Teammates' abilities Teammates' preferences Teammates' tendencies	Low

the knowledge, skills, preferences, and other attributes of their partner, compare Table 2.1. The equipment model is considered quite consistent as the user will handle the object or equipment in a certain manner. The most dynamic model is the team model, which highly depends on the specific partner. A framework on haptic collaboration should embed according mental models and allow for their transformation/adaptation to address the proposed dynamics.

Here, it is assumed that the individual mental models in haptic collaborations need to conceptualize different external counterparts: not only a model of the task but also from the partner, the environment and possibly the object are involved and have to be shared. The models presented in this section emphasize learning in as representations can change with experience and requirements. In the next section, the state of the art in robotic architectures in relation to intention recognition and mental models is presented.

2.1.4 Intention Recognition: Robotics

Intentions are action plans on how to achieve a goal (compare Appendix A), and in contrast to executed, observable actions, intentions are thoughts on actions. This section introduces two exemplary architectures proposed for robots able of intention recognition.

Two different levels are distinguished by Avizzano and Bergamasco [1999] in a "new interactive paradigm", where a *reactive* robot allowing bidirectional skill-transfer is described (compare Figure 2.5). The basis of this skill transfer is seen in intention recognition. A low and a high level

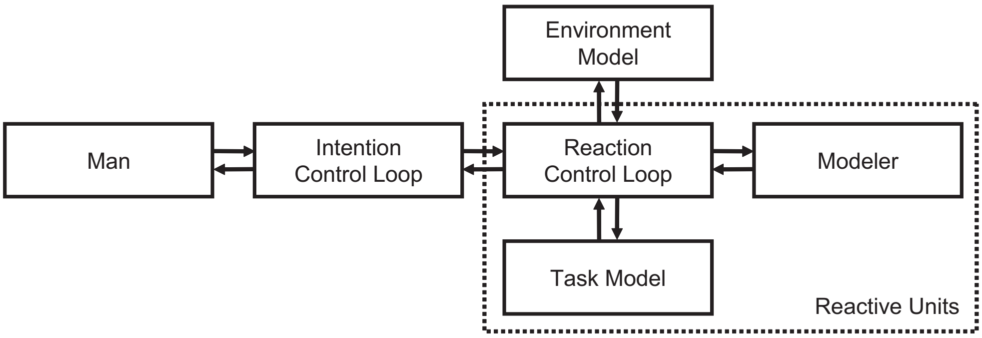


Figure 2.5: Possible architecture for a reactive robot as proposed by Avizzano and Bergamasco [1999]

of signal transfer between human and device are separated. The lower level is not intelligent and only transfers raw data whereas the skill transfer takes place on a higher level. The proposed architecture for such a reactive robot includes a *reaction module* which consists of three other modules (reactive units): a) an *interpreter module*, which interprets the signals from low level and estimates the task b) a *reaction control module* which determines the interaction with the user and distributes information among other modules c) a *modeler module* providing information on the user's intentions, interpreted as goals. The reaction control loop exchanges signals with an environmental model and a task model. In contrast to Johannsen and Averbukh [1993] and in line with Schomaker et al. [1995], the two levels of the robotic architecture exchange information with the user by an identical channel (here vision and haptic). The reactive architecture is implemented in Solis et al. [2007]. The model introduces a robotic partner capable of intention recognition, and explicitly names a teaching haptic interface in contrast to a cooperative partner. Based on recognized intentions of the user on Japanese letters, the robot guides the user along a preprogrammed trajectory to increase his/her performance. The importance of intention recognition is stressed.

The robot "respects" the user's intentions, thus, has no own intentions and therefore, negotiation of intentions is not modeled. However, in haptic collaboration, the two partners may have different ideas on action plans due to their capabilities, personal preferences, or environmental constraints. This model shows that intention recognition is possible by robotic partners and can be considered a valuable reference which can be extended further.

Another architecture is presented by Schrempf et al. [2005], where intention recognition is addressed in the context of a service robot; haptic collaboration is not addressed. In their model, the *intention recognition* module directly interacts with a database and the planner of individual movements, compare Figure 2.6. The intention recognition module builds a model of the human users and thus "allows for estimating the user's intention from external cues while maintaining information concerning the uncertainty of the estimate". The architecture, which has not been implemented yet, enables the robot to proactively interact with the user to gain more information for intention recognition. This model is close to the here presented framework. However, as no continuous interaction is addressed, adaptation towards the partner is not modeled. Adaptation is addressed in Section 2.1.8.

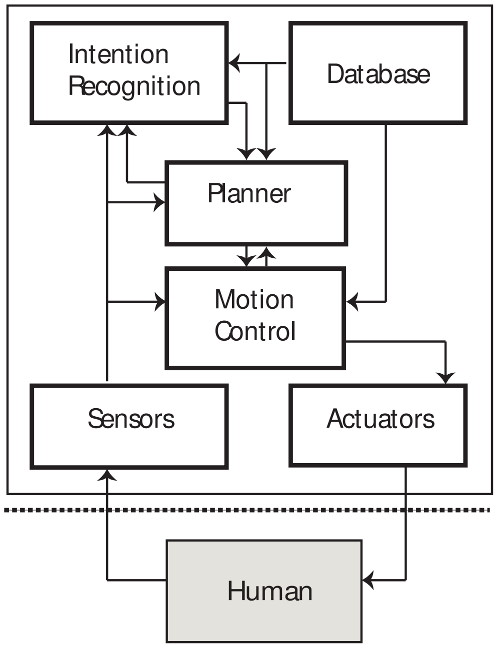


Figure 2.6: System architecture proposed by Schrempf et al. [2005]

Thus, there are existing models for robots dealing with intention recognition on the basis of representations of the users. However, for the framework developed here, these models need to be extended towards intention negotiation between partners which may have different action plans and which have to agree on them. The next section looks into action plans with more detail, namely how actions are chosen to achieve a goal.

2.1.5 Decisions on Actions

Decision making is generally defined as the act of choosing one available option out of several possibilities, which have different trade-offs between benefits and costs. Some researchers refer to decision as the "forming of intentions before acting" [Hardy-Vall?e, in press], whereas others define the exact time-point as decision, e.g. Hoffman and Yates [2005]. Wickens [2004] defines a decision-making task with the following components:
1) "a person must select one option from a number of alternatives".
2) "there is some amount of information available with respect to the option".
3) "the time frame is relatively long".
4) "the choice is associated with uncertainty".

After a literature overview on existing models of decision making Wickens [2004] develops a model of the decision making process based on Rasmussen's model (Rasmussen [1983]). Three levels of decision making are introduced based on the interpretation of environmental cues and the resulting action execution (see also Figure 2.7):
1) *Automatic information* processing: In accordance with the skill-based level in Rasmussen [1983], the relation between perception and action does not need higher cognitive considerations.
2) *Intuitive information* processing: After the environmental cues are integrated, a rule which is

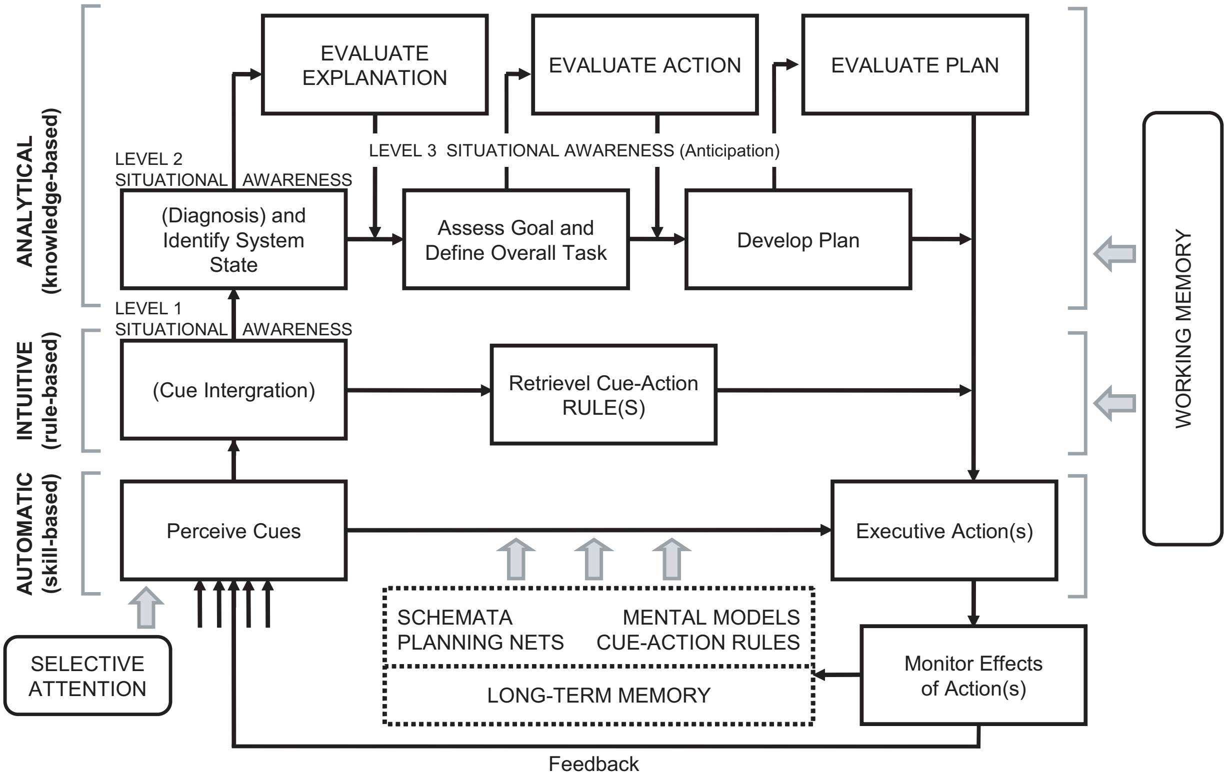


Figure 2.7: Processes in decision making as described in [Wickens, 2004, Chapter 7]

learned in earlier experiences can be activated to generate an action.
3) *Analytical information* processing: When decision time is available or the two lower stages do not provide solutions, analytical (knowledge-based) processes are involved in decision making based on the help of cognitive simulations (mental models) to develop hypotheses about the state of the environment.

The decision process contains *mental models* to make mental simulations possible and evaluate the decisions. Furthermore, the importance of *feedback* is emphasized to correct poor decisions. Thus, this model integrates requirements stated in Sections 2.1.1, 2.1.3 and 2.1.2 into a decision process model. However, a partner is not addressed in the decision process.

For a framework of haptic collaboration it is proposed here that these different layers exist within the two individual partners. One important aspect in collaboration is that decisions on action plans need to be shared with the partner. In *shared decision making*, two partners have to agree on a solution. In the context of human-computer-interaction, Grosz and Hunsberger [2006] introduce shared decision making as crucial for collaboration. It is emphasized that partners may reason differently in decision situations, but that "they must eventually choose collectively". Thus, they may prefer different action plans due to different information bases or perceived options. Shared decision making is the interactive process to negotiate action plans to reach the shared goal. Thus, the second component of decision making claimed by [Wickens, 2004, Chapter 7] that information should be available in a decision process can be extended to information form the partner when shared decision making takes place. Then, the forth component that decision making involves uncertainties becomes even more relevant as one partner has to recognize the intended decisions of the other partner and cannot be sure to do this correctly.

In Cannon-Bowers et al. [1993] it is stated that shared decision making can be understood in relation to shared mental models: effective team performance requires coordination and a "common or overlapping representation of task, requirements, procedure and role responsibility". Shared decision making is considered as a process of "gathering, processing, integrating and communicating information in support of arriving at a task-relevant decision". For a general overview on shared decision making, see Castellan [1993].

In Evrard and Kheddar [2009] decisions are addressed in the context of haptic collaboration between a human and a robotic partner. It is stated that conflict situations between the two partners are likely to occur if their individually intended trajectories are not identical. It is proposed that within a decision process this conflict needs to be negotiated and resolved. However, thus decision processes are not implemented so far. In agreement with Evrard and Kheddar [2009], it is assumed that the process of shared decision making is important in haptic collaboration. The next section will introduce a model directly addressing a partner, which so far was not included in presented models.

2.1.6 Partner

There are few interaction models which specifically take a partner into account. One example is introduced by Massink and Faconti [2002], where a partner is addressed on the group level of the layered reference model for continuous interaction. The model involves the following levels and is depicted in Figure 2.8:
1) *Physical level*: where physical interaction takes place via signal exchange. Information from the environment is processed. If the signals have certain requirements, they are processed to higher levels. On this level interaction is described as continuous. Effective interaction takes place here. Problems can occur when signals from the artificial system are not adapted to human perception capabilities.
2), 3), 4) *Information processing levels*: 2) a perceptual information processing level which integrates cross modal information to achieve temporal-spatial coherence; 3) a propositional level, which mediates between skill-based (lower levels) and knowledge-based (higher levels) behavior on the basis of pattern recognition and learning; 4) a conceptual level which deals with goals, believes, intentions, and task requirements. On this level, conceptual interaction between human and computer takes place. However, this communication has to be refined into physical signals which are exchanged on the physical layer.
5) *Group level*: is explicitly responsible for interaction problems related to the coordination of a task. Social aspects, shared tasks, turn-taking protocols synchronization of activity are handled here.

This model is considered as a valuable reference when developing a framework for haptic collaboration. It not only addresses a partner, but in addition in levels 2) to 4) the authors explicitly refer to Rasmussen [1983], and the general model is further related to Norman [1998]. The conceptual interaction is interpreted as intention negotiation by the author of this thesis, as intentions relate to goals which are the conceptual basis of task execution. In Massink and Faconti

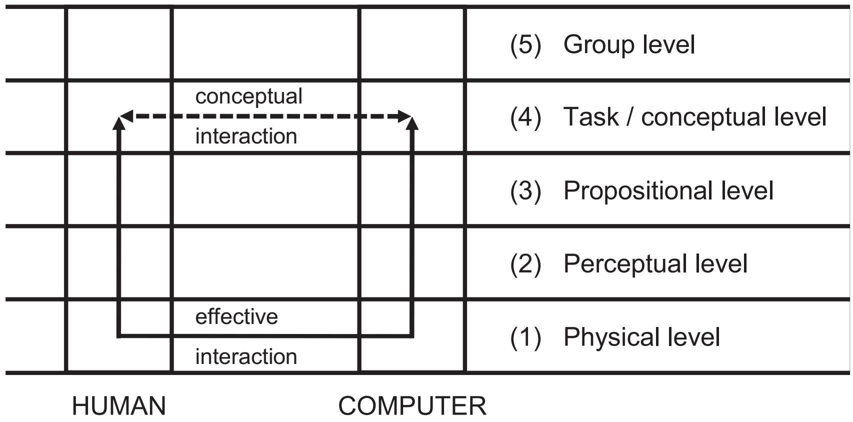


Figure 2.8: "Reference model for continuous human computer interaction" [Massink and Faconti, 2002]

[2002] it is stated that the reference model wants to give design guidelines for continuous interfaces. Even though, detailed modeling techniques are not provided, models from manual control in tracking tasks are mentioned as a possibility to formalize the reference model. Such models are addressed in the next section.

2.1.7 Manual Control Models

To gain information for the implementation of human behavior models on robotic partners the framework for haptic collaboration should be related to control-theoretic models. However, it cannot be the goal to propose detailed parameters as this would be accompanied with a reduced generalizability. The framework should be a basis for as many shared haptic tasks, partners and environments as possible. Signal flows and components required in all of these task should be addressed. Actions in kinesthetic tasks require motor control. Therefore, existing control-models for individually executed manual tasks can be consulted as a reference for the manipulation of an object. In the following, approaches are presented which already integrate components mentioned in the previous sections into a general control loop to execute motor behavior, i.e. feedback loops, different levels of task execution, thus information processing and mental models.

In an overview on models describing human operators interacting with dynamic systems, such as vehicles and aircrafts, generally supervisory control is given. All these models do not assume a partner [Sheridan, 1992]. Still, they deal with trajectory following. It is assumed by the author of this thesis that haptic collaboration is based on the movement of an object or an interaction point, which follows a trajectory. In kinesthetic tasks e.g. object manipulation or guidance, trajectories play a key role because the goal of such tasks can be defined by a position or in the case of e.g. dancing by the trajectory following itself. Thus, the related action plans will deal with options how to best follow such a trajectory. This is in line with the model of "path planning" as basis of human-robot collaboration proposed by Schrempf et al. [2005]. Within the models describing trajectory following presented in [Sheridan, 1992, Chapter 1] is the concept of nested control loops, which is introduced in the context of aircraft control. Sheridan relates to Hess and McNally [1984] when describing such a loop (see Figure 2.9) with a) an *inner* control loop responsible for noise control, b) an intermediate *guidance* loop, which is dealing

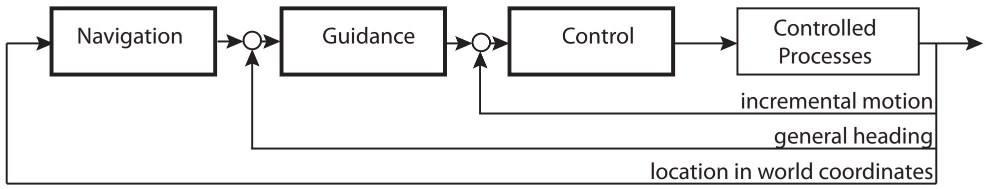


Figure 2.9: [Sheridan, 1992, Chapter 1] relates to Hess and McNally [1984] when presenting this figure, describing "navigation, guidance, and control as nested loops, as applied to an aircraft or another vehicle under multi-level control".

with the general heading of the aircraft and the general fine trajectory inherence, and c) an outer *navigation* control loop which is concerned with planning of gross trajectories. The author strengthens the importance of the concept of mental models for supervisory control. Mental models are necessary to understand the controlled process, to define the objective function and to have general operation procedures and strategies. Here, the supervisory control is related to Rasmussen's framework [Rasmussen, 1983].

Describing pilot behavior from a control-theoretic perspective, McRuer and Krendel [1974] introduce a model for tracking behavior, resembling trajectory following. It was shown that this model can describe the joint performance of two collaborating humans in a tracking task [Feth et al., 2009a]. Furthermore, McRuer and Krendel [1974] list factors which can influence the pilot's behavior. This is of interest as these key variables defining behavior in a motor task can be transferred to the motor task of haptic collaboration: 1) *task variables* address all variables outside the pilot and the control elements. The enormous range of possible conditions is outlined and the direct influence on the pilot's dynamics emphasized. Within task variables a further distinction between 2) *environmental variables* and 3) *procedural variables* is made. The latter ones are defined as aspects of the experimental procedure like training or order of trials. Finally, 4) *pilot centered variables* are introduced e.g. training, motivation, physical condition. The list of these variables resembles the list of mental models proposed by Cannon-Bowers et al. [1993].

It is argued that in haptic collaboration the environment may directly influence behavior as it can provide restrictions influencing the observed executed behavior. In addition, representations of the environment may also influence the parameters in the control of motor behavior before the movement is actually executed. Both paths should be addressed in a framework. Based on such internal representations, discussed as mental models in Section 2.1.3, collaboration can take place by integrating individual action plans. Thus, the two partners have to adapt towards each other as outlined in the next section.

2.1.8 Adaptation

In their overview on human performance in manual control tasks [Jagacinski and Flach, 2003, page 350] state that the classical servomechanism point of view on human performance is not recognizing the "adaptive nature of human performance". It is described that already in simple compensatory tracking tasks humans adopt a control strategy to accommodate the system dynamics. Therefore, the classical control loop for tracking tasks is extended by a supervisory-loop which influences the controller to optimize task-specific criteria. Each level contains a dynamic world model of the environment. This model is then related to the knowledge-, rule-, and skill-based behavior model of Rasmussen [1983] to enforce the authors opinion of qualitative differences between the sub-loops. Thus, not only the adaptive capabilities of humans are stressed, also the possible integration of tracking behavior towards Rasmussen's model is introduced. This extensions of the tracking control loop will play a key-role in the haptic collaboration framework.

Here, it is expected that adaptation does not only take place towards the environment and the controlled object but above all towards the partner gains. However, there is limited literature on adaptation between partners in collaboration. In Johannsen's model (Johannsen and Averbukh [1993]), adaptation of a technical system towards the human is addressed. However, the technical system does not have the status of a partner. It is stated that interfaces should be adaptive to increase the effectiveness of interaction and the users acceptance. For a near-optimal adaptation the following challenges have to be addressed:
a) informative parameters for user modeling have to be selected
b) levels where adaptation is meaningful have to be defined
c) robust metrics to measure the difference between assumed user models and online user behavior have to be identified
d) the laws of adaptation in man-machine interaction have to be identified

These challenges can provide guidelines how adaptation can be integrated into the haptic collaboration framework. They can be transformed for a framework describing the haptic collaboration *between two partners*. Thus, adaptive components are closely linked to intention recognition as the latter provides information about how to adopt to the partner. However, for haptic collaboration the integration of the recognized partner's intentions and own (possibly varying) action plans needs to be specified further.

2.1.9 Summary of Requirements

The goal of this chapter is to establish a framework, which illustrates the processing of information between partners and within partners to accomplish a jointly executed, kinesthetic task. Such tasks include object manipulation as moving or placing and tasks with direct contact between partners as in guidance. It is assumed that the overall task goal, e.g. the goal position for an manipulated object is known to both partners. Several action plans can exist to reach a goal (action plan towards goal = intention). Therefore, a key concept of the haptic collaboration framework is the negotiation of intentions because partners do not necessarily agree on the same action plan a priori. Furthermore, the framework should describe collaboration between two humans as reference for human-like behavior, compare Schomaker et al. [1995]. The behavioral models developed within such a framework can then be transferred to robots as technical partners considering specifications according to the available hardware and tasks. Based on the literature overview above, the following claims on a haptic collaboration framework are asserted:

1) *Haptic Collaboration*: is explicitly addressed here, contrasting other forms of interaction. Thus, signals exchanged by the partners and the environment and between partners are motion or force related.

2) *Feedback Loop and Manual Control Models*: In contrast to pure interaction, shared goals are a key concept to allow collaboration. To achieve goal-oriented performance the components of the framework should address action plans (intentions) and their execution. An action-perception-loop is thus the baseline of the framework based on Parasuraman et al. [2000], where feedback loops allow the evaluation of individual and joint actions [Norman, 1998]. As haptic collaboration is closely connected to individual manual task execution, control-theoretic models established in this line of applications (see Hess and McNally [1984]; Jagacinski and Flach [2003]; Sheridan [1992]) can provide the basis of the haptic collaboration framework. Those control-theoretic tracking task models can then be considered the lower level of interaction as e.g. presented in Johannsen and Averbukh [1993] or Avizzano and Bergamasco [1999].
3) *Levels of Information Processing:* Therein, the goals, intentions and actions should be described by a hierarchical structure of processed information. The framework aims to a close relation to Rasmussen [1983] as a well established model, which has been adopted to supervisory control in guidance by Hess and McNally [1984]; Sheridan [1992] and to decision making by Wickens [2004] both important in haptic tasks. Rasmussen's model is integrated in the work of Johannsen and Averbukh [1993] and Massink and Faconti [2002]. Thus, the differentiation of automatic, rule- and knowledge-based behavior should be transferred to haptic collaboration.
4) *Mental Models and Intention Recognition:* Massink and Faconti [2002] state that individual behavior models are not sufficient to describe interaction. Interaction specific challenges, such as coordination, social aspects, or synchronization of activity, have to be addressed by modules in the haptic collaboration framework. The integration of two individual actions in a shared action plan and the involved intention negotiation have to be addressed by the framework to answer those challenges. Mental models as the basis of intention recognition have to be introduced as described by Avizzano and Bergamasco [1999]; Cannon-Bowers et al. [1993]; Johannsen and Averbukh [1993]; Schrempf et al. [2005]; Wolpert et al. [2003]. The architectures for robots as proposed by Avizzano and Bergamasco [1999]; Schrempf et al. [2005] are a reference how to embed intention recognition in control-theoretic models. However, they need to be extended towards a robot as a partner, which does not only recognize intentions, but actually negotiates them based on its (semi-)autonomously developed intentions.
5) *Shared Decision Making and Adaptation towards the Partner:* Both, adaptation and shared decision making, are closely related to intention negotiation. The partners can have different action plans in mind when confronted with the task or subtask (compare Evrard and Kheddar [2009]), they may also have different capabilities or preferences (compare team models in Cannon-Bowers et al. [1993]). However to successfully accomplish the task, partners have to agree on one shared action plan, as the resulting performance depends on both their inputs. This can be achieved by shared decision making and the willingness to adapt towards the partner. Adaptation towards the partner is considered a prerequisite of high performance especially when aiming for a shared goal (see Johannsen and Averbukh [1993]). The haptic framework should identify the parameters or modules, which are adapted. Thus, it will explicitly address the relation to a partner as proposed by Massink and Faconti [2002], extending existing human-machine interaction models.

2.2 Haptic Collaboration Framework

In this section, a conceptual haptic framework for dyadic collaboration in kinesthetic tasks is proposed based on the requirements investigated in the last section.

The framework is based on the assumption that on a task-independent level haptic tasks (as those summarized in Section 1.1) can be described as a movement along a trajectory, compare also Section 1.3. Depending on the task, the focus lies either on reaching a goal position (e.g. placing an object) or on following an optimal trajectory (e.g. guidance or dancing). The following description will focus on the first case. Within Section 2.3, the generalizability towards other tasks is discussed.

The haptic collaboration framework is depicted in Figure 2.10. It illustrates two collaborating **partners**, jointly manipulating an **object**. The framework presents an architecture of underlying structures relevant to describe the process of intention integration of two human partners[2]. The framework is meant to enhance the understanding of these processes towards a control architecture, which can be implemented on robotic partners allowing them human-like behavior, and thus, intuitive human-robot collaboration. For now, two interacting humans are assumed. The specifications required due to restrictions or variations in the perceptual or cognitive systems when one partner is replaced by a technical system are not considered in detail in this fist approach. The two partners are depicted differently, even though, the characteristics of subsystems and signals flows are considered identical (parameters and specific controllers however, may vary). The motivation for the different depiction is a better overview: In *Partner 2* the *three main units* within each partner are depicted. They will be explained in the next section. The visualization of *Partner 1* is used to give a detailed image of the subsystems within the three main units. These subsystems and the corresponding signal flows will also be described afterwards.

Haptic collaboration takes place within a certain **environment** in which the two partners manipulate an object. This framework is focusing on free-space motions in the context of joint object manipulation. Further extensions towards tasks involving contact forces with the environment are possible. For now, the environment does not present forces associated with contact between the object and the environment. Thus, signal flow from the environment generally refers to non-haptic information: visual and auditory cues (and in case of a technical partner possibly additional sensors).

The *three main units* depicted in *Partner 2* can be summarized as follows: Action plans how to a achieve the overall task goal of moving an object towards a goal position, i.e. the desired shared object trajectory, is developed in the *planning unit*. This desired shared trajectory is sent from the *planning unit* to the *control unit*, where the motor command to execute the planned action is defined. Output is the individual force applied on the object. The *planning unit* exchanges information with the *adaptation unit*, which contains mental models of one's own system, the task, the partner and the environment. It is assumed that the overall goal is not communicated via the haptic channel but known to both partners by other modalities. The definition of the shared desired trajectory and the compensation of deviations from this desired trajectory, both summarized as action plans, require intention recognition. And based on this

[2] It is not assumed that the defined structures and signal flows resemble the human physiological or neurological systems.

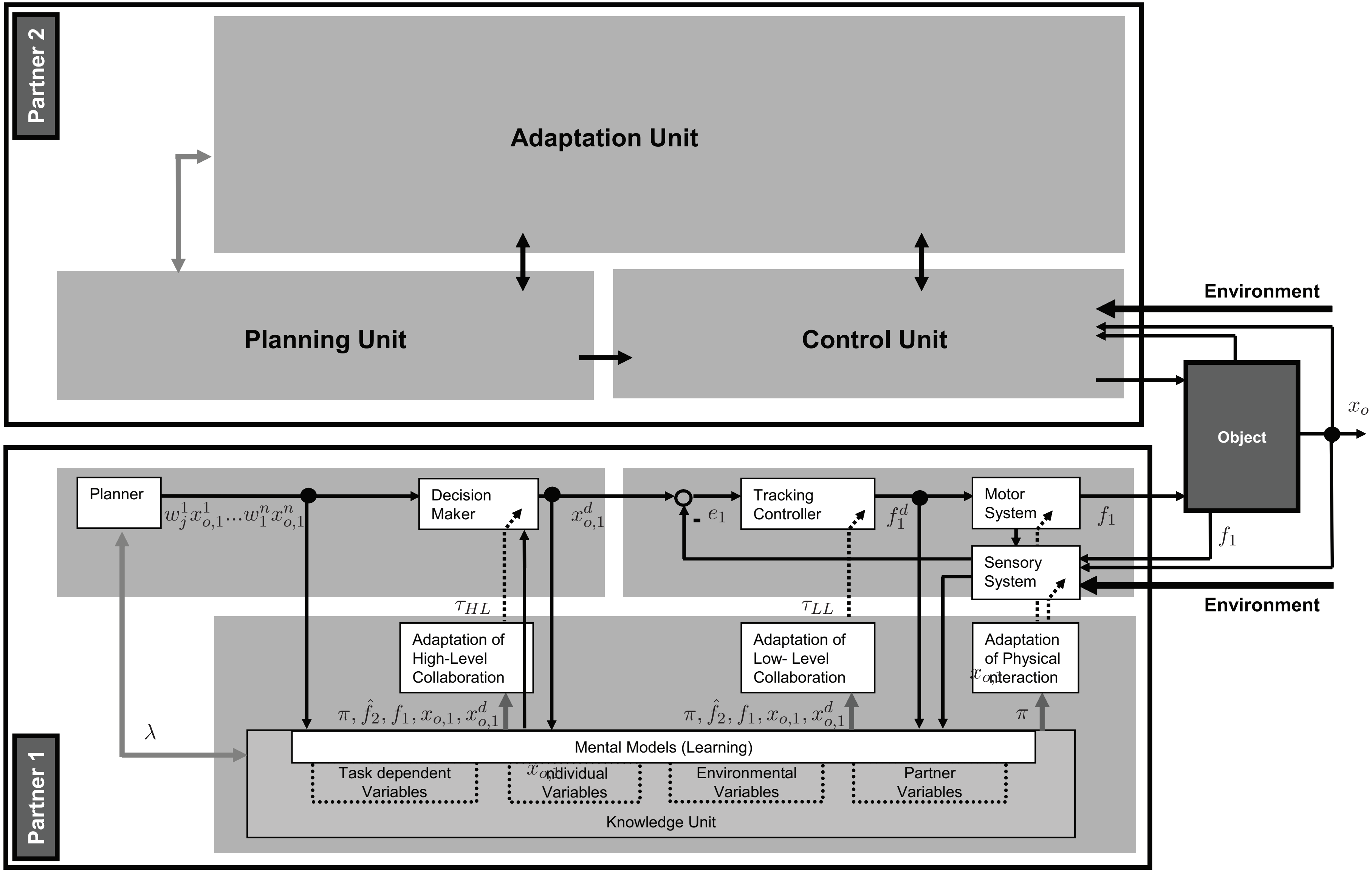


Figure 2.10: The illustration of the proposed framework for haptic collaboration. In *Partner 2* the three main components are depicted, whereas in *Partner 1* a detailed description of the modules and signal flows is given. It is assumed that the architecture is identical for both partners.

and according prediction on the partners behavior, integration and negotiation of action plans between partners and an adaptation towards the partner can be achieved. These processes take place in the *adaptation unit* and are derived based on an interpretation of the signals that are received via the sensory system in the *control unit* comparing the mental models stored there. The *adaptation unit* can then influence the *planning unit* and the *control unit* to realize the adaptations. Now, the units are described in more detail. Note that the processes within one partner are described, here *Partner 1*.

2.2.1 Control Unit

The purpose of the *control unit* is the actual task execution, i.e. to apply appropriate forces on the object keeping it on the desired trajectory towards the overall goal position. It is designed as an action-perception-loop and involves a feedback structure to evaluate the performance, the deviation between desired and actual object trajectory. The control unit consists of the three subsystems: *sensory system*, *motor system* and *tracking controller*.

The input of the *tracking controller* is the tracking error ($e_1 = x^d_{o,1} - x_{o,1}$), the difference between desired and perceived trajectory of *partner 1*. Information about the desired shared trajectory $x^d_{o,1}$ is received from the *planning unit*. Output of the *tracking controller*, the control signal, is the force f^d_1 *partner 1* desires to apply on the object. The force is executed by the *motor system*, leading to a measurable behavior f_1, which due to noise and variable impedances in the motor system is not necessarily identical with f^d_1. Summed with the force applied by the partner f_2, this force is responsible for the object movement, thus the measurable, shared trajectory x_o. This trajectory is perceived by the sensory system. Due to the limitations and characteristics of this system (e.g. bandwidth, resolution, attention) the perceived object trajectory $x_{o,1}$ is not necessarily identical to the real trajectory x_o.

Taking into account Newton's third law it is assumed that the force *applied* on the object by partner 1 is also the force *perceived* by his/her *sensory system*: f_1. There, however, the signal may again be subject to noise. This also results in the assumption that the partner's force is not perceived directly but has to be inferred by relating the object movement to the own applied forces (more information is given when describing the mental models in Section 2.2.3). Furthermore, the *sensory system* perceives environmental information by other modalities than the haptic channel, e.g. the goal or obstacles can be perceived visually; information on the partners behavior, e.g. head movements can be collected and verbal communication between partners could take place. In addition, the *sensory system* has knowledge on configurations in the *motor system*, i.e. proprioceptive feedback.

As the position of the object also depends on the partner's actions, i.e. his/her applied forces, there exist several possibilities how a position error can be reduced by the collaborating dyad. The process of intention negotiation mainly takes place in the *adaptation unit*, but the resulting desired behavior is executed by *tracking controller*: Based on estimations of the partner's force, a strategy is realized defining how much force is applied to execute the desired trajectory. The structure and/or parameters of the *tracking controller*, and thus, the reaction to an existing tracking error, can be changed depending on an adaptation rule defined in the *adaptation of low-level collaboration*. This adaptation component is part of the adaptation unit, described further in the corresponding Section 2.2.3.

The parameters of each of the three subsystems in this unit are not necessarily time-constant. Changes can occur due to adaptation towards the environment and in relation to the physiological system (hardware for robotic partners), e.g. after exhaustion of the muscles or depending on angels in the limb-joints it may be necessary to change the parameters in the *motor system* to follow the desired trajectory. Similarly, the *sensory system* can change its focus of attention or adapt to environmental conditions. These variations are induced by the *physical interaction adaptation component*, again part of the adaptation unit.

The tracking controller is described as position controller, which can be realized e.g. with controllers known from manual task control in tracking tasks, compare Jagacinski and Flach [2003]; McRuer and Krendel [1974]; Sheridan [1992]. Of course, this simple structure can be extended e.g. allowing feedforward in addition. For robotic partners, the specification of motor and sensory system depends on the available hardware. Even though the goal of the *control unit* is clearly specified here, its realization may vary depending on the details considered in the motor system. A profound description of components of this system and their modeling is beyond the scope of this thesis.

2.2.2 Planning Unit

Aim of the *planning unit* is to provide possible goal-oriented object trajectories to perform a given haptic collaboration task. In real-life scenarios, different options for the object trajectory towards the goal may exist, e.g. a goal may be reached by different routes; accuracy or time can have different priorities; constraints in the environment or the partners' capabilities may be answered in different ways. Furthermore, the two partners can have different representations of the task and the environment and their personal preferences can differ. Thus, two modules are proposed for the *planning unit*: a) a *planner*, which examines the possible trajectories and chooses the trajectory perceived as optimal by the individual; and b) a *decision maker*, which chooses a desired trajectory considering the output from the *planner and* the input from the partner to derive a *shared* action plan.

The *planner* receives its input from the *adaptation unit*. Information related to e.g. environmental information on object properties, the goal position, and positions of possible obstacles is transmitted. According signals are first perceived by the *sensory system* and interpreted by the *adaptation unit* and together with the here-stored knowledge on the task goal further transferred to the *planner*. In Figure 2.10 this signal flow λ is depicted in a lighter color to contrast it from more specific signal flows. Qualitative information defined by λ can for example contain information on the perceived physical fitness of the partner. Such information could change the individual optimization rule, and thus, the preferences for possible trajectories. In the given example, if the partner looks weak, the length of the trajectory can be optimized so he/she does not have to carry the object for too long.

Based on this information, the planner can suggest a set of possible motion trajectories to the *decision maker*. It is assumed that these trajectories have a discrete number. Additionally, the *planner* weights these trajectories based on preferences received from the *adaptation unit*. The resulting signal for the *decision maker* can thus be described as $w_j^1 x_{o,1}^1 ... w_j^n x_{o,1}^n$., where $w^1 \dots w^n$ are the *individual* weights of the different trajectories. Note that according to the hierarchical structure of task goals, there can be desired trajectories proposed for these sub-goals. Examples of such discrete options for the desired object trajectory in these sub-goals can be found in obstacle avoidance, i.e surrounding it clock- or anticlockwise.

The *decision maker* selects the individually desired *shared* trajectory for the object ($x^d_{o,1}$). This is done by considering the own preferences, out of the possible trajectories proposed by the planner, and additional input from the partner, i.e. his/her estimated intentions e.g. based on $\hat{f}_2$, the estimated forces applied by the partner. The integration of two different individual action plans towards a shared intention is challenged depending on the deviation between the personal preferences. Furthermore, the actual trajectory ($x_{o,1}$) and the individual force input to this trajectory (f_1) can influence the decision. Thus, there is a feedback loop comparing the desired trajectory with the actually followed trajectory (x_o) via the sensory system. How this information is processed within the *decision maker* depends on the adaptation rules defined in the *adaptation of high-level collaboration* component. Hence, in the *decision maker* intention negotiation takes place, i.e. *shared decision making*. Details on adaptation will be described in Section 2.2.3.

If a robotic partner has to generate possible desired trajectories, the planner can use path planning algorithms and task-dependent optimizations to define the trajectories and the preferences (weights). The optimization rules can be gained from the knowledge base. One decision model which allows dynamic modeling of individual decisions is the decision field theory proposed by Busemeyer and Townsend [1993], see also Busemeyer and Diederich [2002]. This state-space model has successfully been introduced in research on operators in supervisory tasks by Gao and Lee [2006] and a survey for robotic applications is given in Erlhagen and Bicho [2009]. This model seems to be an adequate starting point when defining a concrete decision maker for a robotic partner in collaboration.

2.2.3 Adaptation Unit

The *adaptation unit* forms the heart of the haptic collaboration framework as it addresses the collaboration with and the adaptation towards the partner including intention recognition, integration, and definition of rules to negotiate them. It consists of mental models (stored in the knowledge unit),related predictions, and three different adaptation modules, which influence components in the *control unit* and the *planning unit*.

Mental models

Mental models are introduced within the *knowledge unit* to allow a higher-level control based on internal representations of the task, the environment, the own system, and the partner. In haptic collaboration, it is fundamental to choose task depending optimal action plans to achieve the desired shared overall goal. High performance as well as resource-saving does not only depend on the individual. The partners need to adapt and negotiate their individual action plans towards a shared intention. The *knowledge unit* consisting of the internal representations and predictions, i.e. mental models are the basis for intention recognition and integration. Based on past experiences, input from the *sensory system* and feedback from the signals processed in the *planning unit* and the *control unit*, mental models are built, which can influence adaptation rules as the basis of intention negotiation. Those rules specify the adaptation towards the partner and the environment, and thus, influence the action plans for task execution. As mental models can be advanced and specified based on experiences, learning in haptic collaboration takes place here [Wolpert et al., 2003].

If our goal is to change the environment together with another person, mental models of different aspects need to be formed. They are presented in relation to key variables introduced by McRuer and Krendel [1974] and the models proposed by Cannon-Bowers et al. [1993]. The factors described by [McRuer and Krendel, 1974] are defined with focus on experimental setups and not for real scenarios. He relates to a *single* person's free-space motions. Hence, it is necessary to modify and extend the list to meet the characteristics of *dyadic* haptic collaboration. The transformed definitions of the four influencing factors on mental models are as follows:
1) *Mental representations of the task* represent the goals, related sub goals and possible action plans, which have to be achieved by the interacting team. They are related to the task variables in McRuer and Krendel [1974] and the task models in Cannon-Bowers et al. [1993]. One important aspect of the task representation is to clarify prior to task execution whether it is actually necessary to collaborate or if it can be done alone or if dyadic sequential processes are promising. If the task requires haptic collaboration, different action plans can be formed to combine the two individual inputs to the tasks.
2) *Mental representations of the environment* refer to the way how the state of the environment is presented, mainly by haptic and visual feedback. These representations are associated with the environmental variables in McRuer and Krendel [1974]. In Cannon-Bowers et al. [1993], they are listed within the task model. Here, object characteristics are thought to be part of the environment, summarizing all representations of the external world except for the partner. Thus, the equipment model is associated with this mental representation. Such equipment models may relate to the form of interaction (which can be direct human-human or direct human-robot as well as two humans interacting mediated by a robot as in tele-presence or VR)[3]. Task-specific environmental variables include object characteristics and constraints and possibilities for the trajectory towards the goal. Whether environmental information is task specific or not is decided with the help of the *knowledge unit*.
3) *Mental representations of ourselves* are individual variables associated "pilot-centered variables" given by McRuer and Krendel [1974]. Again, a wide range of constellations is possible here, to name some: general capabilities to accomplish the task and preferences on strategies (e.g. being lazy) as well as situation-specific preferences. In addition, there are personal variables which directly relate to interaction as attitudes towards fair workload sharing or dominance. There is no equivalent mental model proposed by Cannon-Bowers et al. [1993]. However it seems intuitive that the representation of our own capabilities influences how we collaborate with a partner.
4) *Mental representations of the partner* refer to information we have about the partner. Such partner variables are not proposed by McRuer and Krendel [1974] because no collaboration is assumed there. These representations are related to the team interaction model and the team model introduced by Cannon-Bowers et al. [1993]. These two models are not separated as the general interaction style is assumed to be human-like. Possible variations from this schema are

[3] If the two partners interacting mediated by devices (possibly in addition to a real object), all device characteristics such as available degrees of freedom are considered environmental variables because they are not specific for the collaboration: When executing the task alone, the device characteristics would still be perceived. In experimental setups and for the design of technical systems, the definition of coupling between partners which can be rigid or compliant, via an object or direct, is important. The characteristics of the physical coupling between partners are considered environmental variables.

then partner dependent. Hence, the haptic signals and the inferred intentions are most important in this context, but also general information as physical appearance, general capabilities, authority, presumed knowledge on the task, social relation with the partner and related emotions or other variables which may change our mental representation of the partner. Learning takes place in the mental models. Deviations between existing representations and perceived sensory information are detected here and the mental models can be updated accordingly. If no information on the partner is available at the beginning of a collaboration, it is assumed in line with Wolpert et al. [2003] that the individual model of oneself is taken as a reference.

Input to the *mental models* are signals processed by the *sensory system*. These signals are interpreted by the mental models to gain representations of the partner's actions or environmental changes. These interpretation and the resulting representations are assumed to be task-dependent. Thus, the mental models receive additional input from the *planner* on possible trajectories and information on the individually desired trajectory from the *decision maker* and the desired force from the *tracking controller*.

The internal representations built in the mental models have different aims in the context of haptic collaboration: Most important is the inference on the partner's intentions. In Kanno et al. [2003], this is described in detail as the inference on the partners goals based on the observed actions. As the overall task goal is assumed to be known by both partners, this claim can be transferred to evolving sub-goals during task execution. According to Cuijpers et al. [2006], it is most important to identify the partner's goals to allow goal-oriented behavior for the overall system. In haptic collaboration, those have to be inferred from force and position signals. Whereas the position of the object and/or the partner can be directly perceived by the sensory systems, the forces applied by the partner cannot. Instead, one's own forces are perceived and the resulting object movement observed, which allows inferring the partner's forces $\hat{f}_2$. Estimating the partner's intentions is not enough to allow efficient collaboration. The intentions have to be negotiated to find a shared action plan, i.e. rules on how the partner's actions are combined with the own action plans considering task and environment need to be established. In Kanno et al. [2003], it is stated that "team intention is not reducible to mere summation of individual intentions". Those rules are specified in the three adaptation modules. Changes in the mental models can change adaptation rules, e.g. working together with a physically weaker person may lead to a more sensitive adaptation in terms of partner's forces, as the partner is assumed to apply lower mean forces. The information transferred from the mental models to the adaptation modules is represented by π as it is abstract knowledge and no physical measure. However, it is proposed that these rules consider the inferred partner's force $\hat{f}_2$, one's own forcef_1, and the perceived object position $x_{o,1}$ as well as the desired position $x^d_{o,1}$ as input variables. Therefore, these signals are transmitted from the mental models to the collaboration-specific adaptation units. The adaptation modules are described in detail in the next paragraphs.

Internal representations of task are an output of the mental models for the *planner*. They include the overall goal, self-representations and information about the partner and the environment (all described by λ), which allow the planner to find possible trajectories to reach this goal.

Knowledge bases and intention recognition modules are proposed by Avizzano and Bergamasco [1999] and Schrempf et al. [2005] for robotic applications. In Hwang et al. [2006], an information theoretic approach for mental models and its formal modeling is proposed. Thus, there already exist first steps towards an implementation of the required modules.

Adaptation

Based on the mental models in the *knowledge unit*, the individual can adapt structures and parameters in the modules of the *planning unit* and the *control unit* in relation to task requirements for optimal performance. To address this explicitly, three adaptation modules are introduced, which receive information from the mental models and yield a function of how to treat information received by the sensory system. The high capability for such adaptations in humans is shown for manual control tasks by Jagacinski and Flach [2003]. However, their importance increases when collaborating with a partner which requires coordination of two individual inputs and shared decision making.

The adaptation laws in the three modules can have different structures and vary in complexity, starting from simple linear functions and fixed mappings as in gain scheduling to more complex adaptive control or optimization rules, see Astrom and Wittenmark [1994] for an overview. Furthermore, it may be suitable for the design of robotic partners that not only the parameters of the controllers in the planning or the control unit are adapted, but the structure itself is changed, then hybrid models need to be addressed.

Adaptation of Physical Interaction

This module is responsible for adjusting the parameters of the *sensory system* and the *motor system* within the *control unit*. The initial tension in muscles (based on the internal representation of the object), the visual attention focus (again based on mental models about the environment), and other behavioral parameters can be manipulated via the physical interaction adaptation. This adaptation is not part of collaboration as it is assumed that parameter adaptation does not take place on the basis of recognized intentions from the partner. However, it is an interactive adaptation as there is reciprocal influence between partners. Thus, the partner and the related internal representations in the *mental model unit* may change rules in the adaptation module, e.g. the expected weight of the object the individual has to carry varies with the existence of a partner. Another example is given when two people carry a table, and up and down movements due to walking motion from the one partner are perceived by the other. Automatically (in the sense of Rasmussen [1983]) humans balance this movement without any interpretation of the partner's intentions.

The focus of this framework is on collaboration. Therefore, the physical interaction adaptation is not described in more detail.

Adaptation of Low-Level Collaboration

The desired object trajectory cab be the same for both partners ($x^d_{0,1} = x^d_{0,2}$) because it is clearly defined by the task or the environment. Still, it is required that strategies are derived which determine how the overall force necessary to follow the desired trajectory is applied by the partners. The necessary force of the overall system (both partners) can be split in different ways between partners. Within this process, a *low-level adaptation module* is responsible to find adequate ways of adaptation towards the partner's behavior, especially the force applied by him/her in relation to the desired trajectory.

Thus, this module adapts the parameters or structure of the *tracking controller*, which aims to reduce deviations from the desired shared trajectory. For this compensation different action plans with respect to the two individually applied forces are possible. The forces one partner would apply to the object when acting alone, change depending on the partner's actions. To allow a successful integration of the two individual action plans, the parter's intentions have to be estimated. Therefore, this module is described as collaborative. For example, if it is clear how the two partners maneuver an object around an obstacle (high-level collaboration), one partner can still choose to be lazy and leave the main physical workload to the other partner (low-level collaboration). For high task performance, this partner has to realize that he will have to apply more forces based on the internal representation of the partner's behavior and according predictions of his/her behavior. Thus, the negotiation on strategies is accomplished by interpreting the partner's intention based on the mental models and defining an adaptation law in the *low-level adaptation* module. This adaptation process is named *low level* because it is only dealing with action plans when a desired shared trajectory (a sub goal in the overall action plan) is assumed to be agreed on by both partners[4]. Thus, this level is related to the "how"-to-do level proposed by Johannsen and Averbukh [1993]. In the given context it describes **how to move the object**. Which adaptation law is adequate in a given situation is determined by the mental models and perceived signals from partner and environment. Based on the according input, the *low-level adaptation* module defines an adaptation rule. The output of the adaptation module can be either a parameter-vector or a function, if the structure of the tracking controller is adapted. In order to depict both cases, the output signal is not further specified and generally named τ_{LL}, with LL for low level in Figure 2.10.

It is proposed to relate this level of haptic collaboration, where it is defined how to move the object, to rule-based behavior and rule-based decision making in the sense of Rasmussen [1983] and Wickens [2004]: once a model of the partner is developed and his/her intention recognized and integrated in the individual action plans, collaboration on this level should be smooth based on the roles chosen by the partners (e.g. leader and follower). This decision is assumed to be implicit. The information on the partner is perceived as signs which trigger adequate actions to keep the object on the desired trajectory. Or, as Wickens [2004] states it, the partner's input is an *if-then-rule*, which defines the necessary output to achieve the shared goal.

The author of this thesis is confident that dynamic models of social interactive behavior known from humanities can be adopted to approach specific control architectures for this adaptation component focusing on partner's signals, e.g. Felmlee and Greenberg [1999]; Gottman et al. [2002]; Liebovitch et al. [2008]. These theories are not based on kinesthetic data and do not take into account continuous haptic coupling between partners which is a specialty of haptic collaboration. However, according transformations could be defined.

[4] If the two desired trajectories are not identical, the negotiation of a jointly desired trajectory takes place on the higher level of haptic collaboration as described in the next paragraph

Adaptation of High-Level Collaboration

Preferences on the desired object trajectory out of several possibilities are not per se identical for both partners. Shared decision making may be necessary. The *adaptation of high-level collaboration* contains adaptation rules depending on the partner's action to consider his/her intentions in the decision processes on the desired trajectory. High-level haptic collaboration is required, whenever the shared trajectory of the object in a collaboration scenario is not clearly defined. Physical constraints as individual workspace restrictions, within the environment or in relation to the object characteristics have to be considered in the processes of haptic shared decision making as well as performance- or effort- (mental or physical investigation of resources) optimal solutions. There can be large differences between the amount and kind of information on these factors accessible by the partners, especially in human-robot-collaboration. The higher the deviation between the mental models based on this information between partners is and the higher the deviation between individual constraints, the harder it will be to agree on one shared decision.

In contrast to the low-level adaptation to the partner, in this high-level adaptation process not the individual input of the shared object trajectory is treated (strategies how to move the object) but the decision on a shared trajectory itself, which can be related to sub-goals in the action plan to accomplish the overall task. Hence, the *high-level collaborative adaptation* module is responsible for decisions on **where to move the object - along which trajectory**. Thus, the module provides adaptation laws for the *decision maker*, again based on mental models. As it is likely that the partners have different notions on what is the optimal object trajectory (taking also into account the task, the environment, and the personal capabilities and preferences), negotiation on the shared trajectory may be required, see also Evrard and Kheddar [2009]. Again, intention recognition is involved to understand the partner's action plans. Thus, high-level adaptation is defined as a collaborative process. This adaptation to the partner is compared to the "what"-to-do level proposed by Johannsen and Averbukh [1993]. To give an example, two partners jointly carrying a heavy object and standing in front of an obstacle are considered. In relation to his/her information on the environment and personal preferences one partner may want to surround the obstacle on the left side. However, when the other's forces are applied in the opposite direction he/she may change the decision and follow his/her partner to the right side. Information flow in this module is the same as in low-level adaptation: based on mental models and the inferred partner's intentions the adaptation law is defined. On high-level haptic collaboration the adaptation towards the partner influences the *decision maker* by forwarding the adaptation law as a parameter vector or a function to change the structure.($\tau_{HL},$ with HL for high level).

It is assumed that the individuals plan an object movement as an ideal trajectory. Small deviations may be accepted or controlled by the *control unit*. It is further supposed that there exists a threshold, when an executed object trajectory is no longer considered identical with the planned trajectory. Then, a decision hast to be taken, whether a discrete adaptation of the desired trajectory is required. Furthermore, it is assumed that there exists a rule how to treat information of the partner. Again, a threshold could exist: If the partner pulls or pushes away from one's own desired trajectory, high interactive forces (opposite forces of the partner compare Section 4.3) are a consequence. In order to reduce the physical effort, based on the believe that the partner has good reasons for another trajectory, or other social reasons, the personally preferred decision can be changed (e.g. towards a compromise) if these interactive forces increase above a certain threshold. It may be suitable to change this threshold depending on how goal-oriented the partner's behavior is perceived. Finally, the preference-weights of a specific trajectory can be changed this way. These thresholds or alternative functions on the adaptation towards the partner in relation to the environment are part of high-level haptic collaboration. Further, the shared decision on the desired trajectory is related to Rasmussen [1983] symbol level, and thus, knowledge-based decisions as described by Wickens [2004].

There exist several approaches towards the modeling of collaborative behavior in shared decision processes. For example with a game-theoretic approach, Hill et al. [2005] modeled decisions by cooperative pilots and Xiao et al. [2005] decisions in engineering teams. Decision making is formally described in multi-agent systems in Panzarasa et al. [2002]. An extension of the dynamic field theory of decision making (Busemeyer and Townsend [1993]) could be advanced towards shared decision making. These approaches are described as valuable reference, however, they have to be adopted to continuous, haptic connection between partners.

2.3 Discussion of Framework

In the following the haptic collaboration is discussed. First, the proposed framework is related to the requirements derived from the literature overview in the first Subchapter 2.1. Therein, it is especially referred to the claims summarized in Section 2.1.9. Second, possible extensions of the framework are discussed.

2.3.1 Statement on Requirements

In haptic collaboration, the information which can be exchanged between partners is force- and motion-based (claim 1). The proposed framework addresses haptic collaboration explicitly by describing force and position signals and their exchange between specific modules. It is additionally referred to further modalities when task relevant, e.g. visual feedback from the object trajectory. Some simplification on exchanged signals had to be made, e.g. physical adaptation is not described in detail as it is assumed that the processes taking place here are based on several modalities and require task specific psychophysical knowledge. The same simplification holds true for more qualitative signals processed in the knowledge unit. Again, it is assumed that this signal flow is complex and modeled more easily in concrete scenarios which allow focusing on specific high-level variables. The framework provides guidelines to derive a model of haptic collaboration, including the identification of specific parameters.

The second claim in Section 2.1 addresses the control of executed actions. The framework clearly separates an executing control unit and a planning unit. The former contains a direct feedback structure in an action-perception loop and can be realized with control-theoretic models known from manual tracking tasks. Thus, the structure of the control unit enhances the transfer of established models for individual behavior from this line of research into new collaborative models. Within the control unit a feedback loop from the sensory system allows for continuous reduction of deviations from the desired object trajectory, compare Norman [1998]. The control unit is part of *low-level* haptic collaboration as it focuses on the *how*-challenges within a given action plan (Johannsen and Averbukh [1993]). The decision maker closes another feedback loop. Based on information of the partner's behavior and the goal-orientation of the

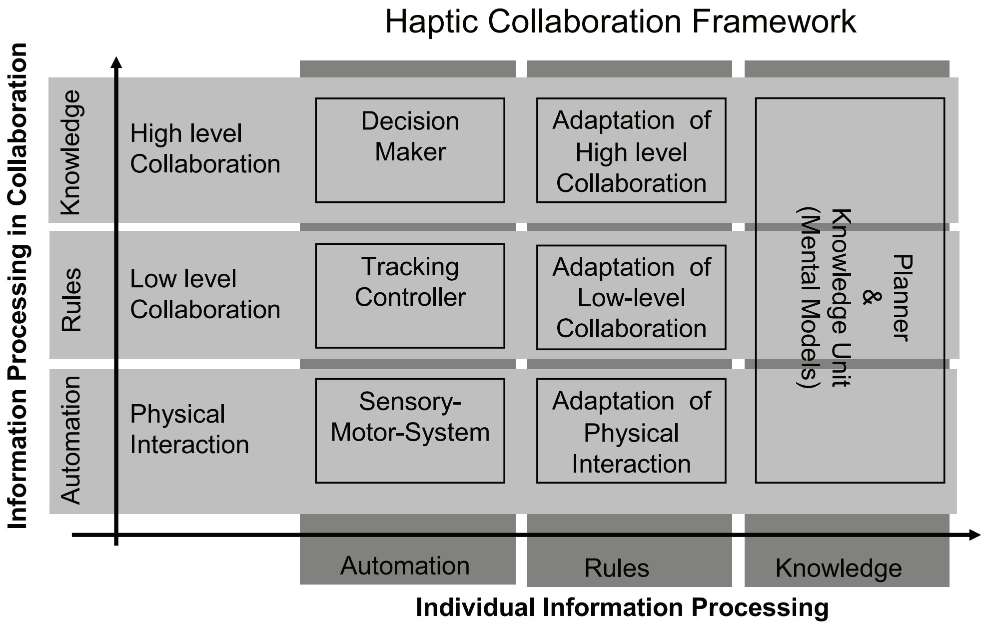


Figure 2.11: Informations in haptic collaboration is processed on different levels in the sense of Rasmussen [1983]. To accomplish a shared haptic task the individual processes informations on the sign, signal and knowledge levels (according to automation, rules and knowledge) for successful performance in the environment. For collaborative task execution Rasmussen's model is described with two dimensions here: The three different levels describe a) process in relation to the task (vertical); and b) in relation to the partner and the environment (horizontal), i.e. adaptive processes. Both dimensions display the SSK-structure (sign, signal and knowledge levels). This illustration is a simplification and does not want to imply that the two dimensions are independent of each other, nor that the modules are clearly distinguishable.

current object trajectory decisions on the desired trajectory can be changed. The planning unit is part of *high-level* haptic collaboration and associated with the *where*-challenge when planning the task (comparable with the what-level in Norman [1998]).

When surveying existing literature on information processing in human-machine interaction, a hierarchical structure is proposed by several authors e.g. Wickens [2004]; Johannsen and Averbukh [1993]; Massink and Faconti [2002], where most of them relate to Rasmussen [1983]. It is proposed that Rasmussen's model including the sign-, signal- and knowledge- levels (SSK model) holds for *two* dimensions within the haptic collaboration framework, in contrast to its original one-dimensional description of information processing for individual task execution, see Figure 2.11. *Signals* are processed automatically in physical interaction with the environment. On low-level task execution, deviations between the desired and actual trajectory are reduced rule-based and information is processed as *signs*. *Symbols*, are proposed to represent knowledge required for high-level task execution. This structure is in line with the multi-level control loop proposed in Hess and McNally [1984], see [Sheridan, 1992, Chapter 1].

In addition, the haptic collaboration framework provides a similar structure concerning information from the partner (horizontal axis): The tracking controller and the decision maker automatically process *signs* from modules of the adaptation unit and feedback from the partner. The rules how to react to the partners are defined in the adaptation modules considering input form the partner via the knowledge unit which can trigger these rules. Thus, information about the partner is processed as *signals* here. The knowledge unit processes more abstract information on the basis of mental models of the partner and can influence lower levels based on the processed symbols. Hence, the processes of *intention negotiation*, from intention recognition to adaptation rules and actual changes in action plans, can be related to the three levels of Rasmussen's model. The two dimensions in Figure 2.11 both represent how information from the environment (including task specific information and the partner) are processed. With the adaptation unit the claim to provide group specific information processing (see Massink and Faconti [2002]) is addressed within the haptic collaboration framework.

Mental models as asked by Johannsen and Averbukh [1993]; Wolpert et al. [2003] are represented in a knowledge unit and specified to four sources of information. One of them representing information on the partner. This mental model is the basis for intention recognition as already proposed for robotic architectures by Avizzano and Bergamasco [1999]; Schrempf et al. [2005].

Adaptation is explicitly part of the framework as required by Jagacinski and Flach [2003]; Johannsen and Averbukh [1993] as well as shared decision making compare Cannon-Bowers et al. [1993]; Grosz and Hunsberger [2006]. To allow not only intention recognition but also negotiation (if the two partners have differing action plans due to environmental constraints, preferences in task execution, capabilities et cetera) the partners actions have to be integrated in the individual task execution. This is illustrated in the framework via the adaptation modules, which influence the tracking controller (*how*, *low-level*) and the decision maker (*where*, *high-level*) towards shared action plans leading to high performance. Thus, the two levels in Johannsen's model could be integrated in one single process of information exchange. However, the two components of communication and supervisory control are still distinct and can be separately addressed in research and the development of robotic partners. Herein the challenges Johannsen and Averbukh [1993] associated with adaptation processes are investigated. The haptic signals from the partner are considered to transfer information. The levels of this information are structured by Rasmussen's model. The remaining challenges to measure adaptation and define adaptation laws have to be subject of experimental research and modeling.

2.3.2 Extensions

First, it has to be mentioned that this framework is the first approach towards a description of processes taking place during haptic collaboration between human partners. As such it is assumed to be transformed in future when more knowledge from experiments based on related tasks is available. This implies further, that the distinction between the levels should not be interpreted to strictly as it is seen as a tool for modeling complexity which may be more fuzzy in reality.

The framework is introduced for scenarios requiring shared *object manipulation*. With the objective to generalize this framework towards haptic interactions with direct contact between partners (e.g. contact between two hands as in guidance), the object can be defined as zero-object, then, named interaction point. Further, the object may be virtual or tele-present. Hence, there may be devices mediating the human output applied on the object. Within the framework, the actual object and the device can be merged as one component. It is important to note that the characteristics of the object (e.g. size, stiffness) influence the physical connection and thus, signal transfer between the partners. This is also true for the devices, which may influence collaboration e.g. by restricting the workspace to a limited number of degrees of freedoms. Keeping the framework as general as possible, such object and device characteristics were not specified. Furthermore, the framework does not consider contact between the object and the environment. This additional source of forces affecting the object can be modeled additionally for concrete tasks.

As stated earlier, the framework is based on a position controller in the control unit. The assumption that the goal of haptic collaboration tasks is the execution of a position trajectory should hold for most scenarios. If, however, a force trajectory is a better model of the task goal (e.g. in rehabilitation applications), the signal flows can be transformed accordingly. It is assumed that it is possible to change the framework towards this need if required. It is proposed to do this together with object characteristics in the context of a specific task. Another simplification in the framework lies in the neglect of possible time delay in the signal flow between the components. The disregard of predictive control is closely related. This is in line with the state of the art in all interaction models introduced in Section 2.1. However, time delay will be of importance when modeling of empirical data is done on the basis of the framework. Then, these factors have to be modeled, which again should be simpler within task-specific considerations.

The integration of the haptic collaboration framework into larger scenarios which require other forms of communication using different modalities is left aside. The task-goal is assumed to be known to both partners, probably on the basis of verbal communication. It is proposed that it is not beneficial to add further interactive components before understanding of haptic collaboration itself has increased. However, the framework can generally integrate other forms of communication. The multi-modal integration of sensory information is a topic studied in psychophysics (e.g. Ernst and Banks [2002]), which is of relevance in the sensory system and mental models. This integration will gain the more importance the more modalities are involved. Psychophysical studies can also help to specify the processes taking place in the sensory and motor systems.

2.4 Conclusion

2.4.1 Summary

This chapter introduced a framework for haptic collaboration between two partners. Requirements for individual processes leading to collaborative behavior, i.e. task performance, have been identified within an overview of existing interaction models, mainly derived in the context of human-computer interaction and supervisory control. Thus, the relations between existing models and haptic collaboration are discussed, before the haptic collaboration framework has been presented in the next step.

The actual framework specifies components and signaling flows involved in haptic collaboration, which can now be addressed more systematically by experiments as done in the remaining chapters of this thesis. Three units are separated: a planning unit, a control unit and an adaptation unit. Depending on the involved structures for task execution within these units, two levels of haptic collaboration can be distinguished: On the lower haptic collaboration level, the partners are concerned with the question of **how** to move an object along a desired trajectory towards a goal position. Low-level haptic collaboration involves the control unit, which is responsible for the application of required forces. The control unit is adapted towards the partner by the adaptation unit to allow intention negotiation, and thus, the development of a shared action plan. The higher level of haptic collaboration deals with the challenge to derive a task-optimal desired trajectory (**where** to move the object). This is the task of the planning unit, which elaborates possible trajectories and chooses the optimal shared desired trajectory. Herein, it is required to process information from the adaptation unit again to adapt to environmental constraints and information perceived from the partner's behavior.

The haptic collaboration framework has been discussed in relation to the requirements defined based on existing models beforehand. A central point within this discussion has been the extension of Rasmussen's sign, signal and knowledge levels for information processing towards a two dimensional representation. These two dimensions of information processing can be found in the corresponding structures within the haptic collaboration framework. Possible extensions of the framework have been outlined additionally.

The framework enables researchers to focus on the identification of different components within haptic collaboration. Modeling attempts as well as psychological experiments can be defined and planned more systematically in relation to these components. In general, the framework enhances the communication, integration and comparison of results from these models and experiments. Existing studies can be classified by the framework, allowing a more profound theoretical background before new ones are developed.

2.4.2 Future Work

The framework addresses the requirements elaborated in the respective sections (summarized in the claims in Section 2.1.9) when describing goal-oriented behavior in haptic collaboration. However, there is awareness that the framework is so far not based on empirical data. The relation to existing models can not be seen as sufficient validation. Thus, future work has to validate the haptic collaboration framework further. Still, it is concluded that based on the answers to the requirements, the framework can be considered as a promising starting point to broaden the understanding and research of haptic collaboration. The framework is not considered to be at its final state. Future research can lead to knowledge which will concretize and possibly transform the framework and lead to further research interests within haptic collaboration. This framework is seen as a first important step to motivate such research.

The next step to validate the framework and to further identify structures and signal flows is seen in experimental studies investigating collaborating humans. Such experiments should address low- and high-level haptic collaboration within a standardized task to address the existence of two levels of haptic collaboration and to understand implications of the two levels for behavioral models.

Some challenges which become evident within the framework are addressed by studies in the remainder of this thesis. Separately the two levels of haptic collaboration are investigated to ascertain whether intention integration actually takes place via haptic feedback as a first step to give meaning to this framework. Then, the two levels are validated in the context of dominance distributions between partners when jointly executing a task. The corresponding results will present first indications for the existence of two separate levels.

2.4.3 Implications for Modeling of Robotic Partners

The main statement of the framework is seen in the separation of low- and high-level haptic collaboration and the introduction of the associated modules. This allows the study of the adaptation modules within the planning unit and the control unit iteratively in experiments. Thus, the level of haptic collaboration can be increased stepwise. Hence, the challenges involved in the understanding of adaptation processes can be reduced. As outlined by Johannsen and Averbukh [1993] these challenges are to measure adaptation and to find generic laws. Within the framework, experiments can be conducted to gain empirical data for modeling of robotic partners including the identification of parameters and signal flows responsible for adaptation.

As pointed out in the description of the modules within the framework, models exist which can be seen as reference structure for these modules: The control unit has been described together with a concrete signal flow and can therefore be related to models from manual tracking control. Furthermore, path planning and decision making models are described specifying the planning unit. However, the modules described within the adaptation unit allow only vague specifications of exchanged signals between them. This bears the challenge to identify the partner's intentions based on haptic signals building a mental model from the partner (see Wolpert et al. [2003] for details). In line with the argumentation in Wolpert et al. [2003], that when there is no mental model available from the partner's behavior, one's own model is taken as reference, it is argued by the author of this thesis, that the robotic partner should show as human-like behavior as possible. Then, we are able to assume a human model as mental representation. Thus, future work should focus on the study of human partners in collaboration to identify the signal flow in more detail by experimental research in specific tasks.

The goal of existing and future experimental studies in haptic collaboration is the identification of key-factors in this context. Once this can be done for (parts of) the framework, a model which can be implemented on a prototype for a technical partner can be derived. Then, experimental studies on haptic collaboration between this prototype and a human partner can be conducted within the framework. These studies can enable a systematic variation of parameters and the investigation of resulting changes in the human partner's behavior and overall performance. This way, causal relations between parameter sets and control architectures and the quality of collaboration are possible. In addition, the separation of haptic collaboration levels allows a clear definition of the capabilities of existing robotic partners and helps to structure evaluation studies.

One major challenge in realizing a model for a technical partner on the basis of the proposed framework lies in the fact that signals from the partner can only be estimated. They can be the result of a decision process *or* a certain strategy for tracking control within the partner (the clear distinction between the levels of collaboration is not necessarily possible here). Therefore, it will be challenging to find quantitative indicators for the interpretation of these signals. Nonetheless, this is a key-prerequisite for successful collaboration. In the author's opinion, the framework manages to point out these challenges and motivates research in this direction.

3 Discussion on Trends in State-of-the-Art Experiments

Psychological experiments can support the acquisition of knowledge towards robotic partners, which are able to collaborate in haptic task via an intuitive manner for the human users. As psychological experiments help understanding the human users' behavior in these tasks, their results can provide guidelines for the design of robotic partners. Furthermore, user studies are employed to evaluate technical partners. So far no state-of-the-art overview exists on the use of psychological experiments in the design of robots for haptic collaboration with humans. Therefore, this chapter provides a discussion about trends in psychological experiments in this context [1].

The following overview on haptic collaboration experiments does not focus on explicit results, but stresses general trends in this research area and identifies general components of the conducted experiments. A sound discussion of individual studies and results relevant for the experiment conducted as part of this thesis can be found in the beginning of Chapter 5 and 6. The studies on haptic collaboration, on which the following discussion is based, are summarized in the overview-table in Appendix B. There, 54 experiments are described citing a total of 82 studies, which can be classified as follows:

- Experiments, which deal with *synchronous* haptic collaboration (in contrast to passing an object, sequential interaction or communication on the basis of artificial tactile signals).

- Studies, which investigate a) collaboration between two humans (directly or technically mediated); and b) human-robot collaboration with autonomous robots or human-like assistance functions (other assistance functions as e.g. virtual fixtures are excluded).

- Experiments are included if the authors referred to them as experiments (though, in evaluations designed as case studies this word can raise exaggerated expectations).

- The studies, which are cited additionally to the 54 fully reported experiments, are those which present results reported similarly in one of the fully reported studies.

To the best of the author's knowledge the experiments reported in Appendix B are all published studies under these criteria at the given time.

After defining psychological experiments, major characteristics of existing experiments are discussed. This chapter ends with a conclusion on the state of the art in psychological studies on haptic collaboration.

[1] In this thesis, the word "experiment" refers to psychological experiments only, knowing, that this is not the only form of experiment important in the context of human-robot interaction.

3.1 Psychological Experiment for the Design of Robotic Partners

Before directions in the state of the art of experiments in haptic collaboration are investigated, a short definition of psychological experiments is given and their meaning within the design process of robotic partners outlined.

3.1.1 Definition of Psychological Experiment

In the way as it is conducted nowadays, the scientific method of experiments was proposed first by Bacon [Bacon, 1926]. Wundt was the first scientist who stressed the meaning of experiments in psychological research [Butler-Bowdom, 2006]. In general terms psychological experiments can be defined as follows: "In an experiment, scientists manipulate one or more factors and observe the effects of this manipulation on behavior" [Shaughnessy, 2008]. The different levels within manipulated factors (also named independent variables) are the experimental conditions. The effect of a manipulation in one factor is assessed by measures of behavior, which in the widest sense can include physiological data, behavioral information or answerers to items of questionnaires. These measures are also termed dependent variables. In order to understand if found differences in measures are systematically due to changes in experimental conditions or caused by any noise, inference statistical analyses are required. They relate the found effect to the unexplained variance (noise) in measurements. Thus, experiments in psychology do not differ in their approach of knowledge-generation compared to other disciplines. However, the complex behavior of humans demands extended care for unsystematic variance and disturbances in the experimental execution (extraneous variables). When conducting a psychological experiments the following steps are undertaken in line with the definition of experiments (these requirements on experiments as first outlined by Wundt [1874]):

- Intentional preparation and selection of experimental conditions
- Control for unsystematic influences and differences between participants
- Systematic variation of experimental conditions
- Observation of effects [on measurement] due to variations in experimental conditions

Within the discussion of the state of the art in experimental research on haptic collaboration, which is presented throughout this chapter, further details on psychological experiments are provided. However, it is beyond this thesis to give an extensive overview on methods of experimental design and analysis. The interested reader may consider Field [2009]; Field and Hole [2002]; Groten et al. [2009d]; Howell [2007]; Rubin and Chisnell [2008]; Shaughnessy [2008]; Tabachnick and Fidell [2006a,b]; Tullis and Albert [2008].

3.1.2 Psychological Experiments in Design Processes

Design processes for interactive systems can generally be described by the following four steps, compare e.g. Butler et al. [2007]; Sharp et al. [2007]; ISO 9241-210 (former ISO 13407):

1. Identification of requirements
2. Design
3. Development
4. Evaluation

These steps are now interpreted for human-robot collaboration: A fundamental step is to identify requirements, which have to be met by the robot. This implies not only an understanding of the task but a profound knowledge about the human partner. This can be achieved by conducting experiments. Possibilities to integrate this knowledge in the control architecture of robots are considered in the second step. Afterwards a prototype can be developed. The matching between the requirements and the performance of the prototype are investigated in the last step, again this can be done experimentally. Note, that this can be an iterative process based on evaluation results. The actual development of a robot (step three) classically belongs to the science of engineering, as well as the system evaluation from a technical point of view. However, a user related evaluation of robots is mainly executed with psychological methods. Within the context of human-robot collaboration the first two steps in the design process require a close collaboration between engineering and psychological science: Each discipline has different methods to derive knowledge and models on the partners in human-robot collaboration.

Thus, there are *two* levels in the design process of robotic partners in haptic collaboration, which can be enhanced by psychological experiments: a) fundamental knowledge on the user's behavior, capabilities and preferences can enhance the hard- and software design in terms of requirements which have to be met (step 1); b) evaluations of existing robots with potential users allow feedback on achieved progress (step 4).

In the following, it is investigated in which ways psychological experiments are employed in haptic collaboration to date.

3.2 Development of Interdisciplinary Work over Time

As a first step to gain insights into experiments used in the research field of haptic collaboration, the development over time of publications presenting psychological experiments in this context is depicted in Figure 3.1. The first experiment is dated back to 1994 (conducted by Ikeura et al. [1994]), since then an increasing trend in the numbers of publications can be found (There are more experiments expected for 2010[2]). However, compared to other fields of research, the total number of 82 studies including all publications mentioned in Appendix B shows that experimental research on haptic collaboration is still young. One implication for current studies is the lack of pre-knowledge when addressing new research questions and designing experiments. Thus, it is not surprising that most current studies have an exploratory character.

[2]This dissertation was handed in on 4th of October 2010.

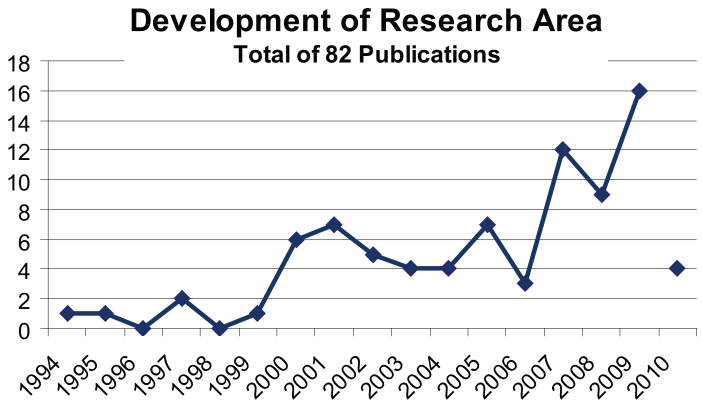


Figure 3.1: Number of publications per year reporting experiments on haptic human-robot interaction, compare Appendix B

3.3 Classification of Research Interests and Measures

In this section the motivation to conduct psychological experiments in the field of haptic collaboration is investigated by classifying the research interests and summarizing the employed measures reported in the 54 main studies summarized in Appendix B.

Research Interests: Six classes of research interests could be identified, compare Figure 3.2. If reported studies had several research interests, those where counted separately. In total 76 research interests were examined. The percentages given in Figure 3.2 and reported in the following, however, are calculated in relation to the 54 main studies to allow statements on the percentages of research interests in relation to the number of publications.

We can see that 44% of studies in haptic collaboration research take place late in the design process, meaning that they deal with the evaluation of existing setups/artificial partners. Three research interests are addressed with similar frequency in existing literature on haptic collaboration: dominance (26%), feedback (26%) and partner (30%). These experiments focus on effects of these factors on human behavior. Thus, there aim is to gain fundamental knowledge on human behavior in haptic collaboration. Herein, dominance-related studies investigate the distribution of control, i.e. the influence of each partner on the jointly manipulated object, when executing a haptic task together. It is assumed that the dominance is of such interest because this aspect becomes more evident in haptic collaboration than in other forms of interaction i.e. verbal communication or other sequential interaction. The two individual actions of partner's plans are combined synchronous and continuous in haptic collaboration, which makes integration of individual actions towards a shared goal a major aspect in this kind of collaboration. Dominance measures, how similar the degree of responsibility for the shared goal is between partners. Furthermore, dominance is a key concept in training scenarios, where a trainee should gain more independence from the trainer (higher dominance in the task) within the learning process. The other two research fields focus on the effect of additional haptic feedback (mainly in addition to visual feedback conditions where no haptic feedback is given at all) and the effect of performing a task alone or together with a partner. Hence, they analyze the effect of haptic collaboration by contrasting it to these control conditions. The related studies address how

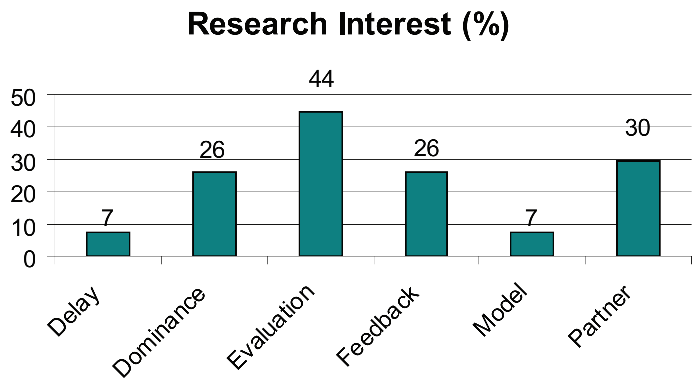


Figure 3.2: Research interests investigated in the 54 publications presented in the state-of-the-art-table in Appendix B. If several research interests are investigated in one study, they are counted separately, leading to a total amount of 76 research interests. The percentages reported here are calculated in relation to the number of investigated publications (54).

measures (mainly performance) changes when haptic collaboration takes place compared to these control conditions. The interest in the effect of feedback and the partner hint towards an interest in fundamental knowledge on principals of haptic collaboration: What changes if haptic feedback is provided and a task is done with a partner? Research interest in time delay (7%) is above all motivated by tele-present scenarios. These scenarios have to deal with the challenge of network latencies, and thus, it is crucial to know how this factor influences the collaboration between partners. This knowledge can then allow to predict consequences in human behavior or find adequate ways to compensate time delay. Striking in this overview is the fact that only another 7% of the investigated studies have the goal to gain information on potential dynamic models of human behavior in haptic collaboration. Models describing human behavior over time are a prerequisite for direct transfer of human behavior models on robots. The small number of studies toward dynamic models is interpreted as a lack of fundamental knowledge on human behavior in haptic collaboration. So far, the state of the art seems to be concerned with knowledge on the general role of the haptic channel contrasting precise modeling of behavioral patterns.

Measures: The research interests determine the experimental conditions to address a certain topic (e.g. partner vs. single person task execution and variation of provided feedback). Furthermore, they require measures, which give insights to changes between these conditions on variables of interest. Figure 3.3 gives an overview on the measures involved in the existing experiments on haptic collaboration. If studies used several measures, those were counted separately. This results in an absolute number of 90 different measures investigated. Percentages are reported as a fraction of the 54 studies independently listed in Appendix B.

In accordance with the goal of performance-optimal collaboration, 61% of the investigated experiments address performance measures. The low percentage of subjective measures (questionnaires: 15%) in these studies can be explained by the fact that behavioral measures are considered more reliable than those. Even more important, behavior can be recorded continuously

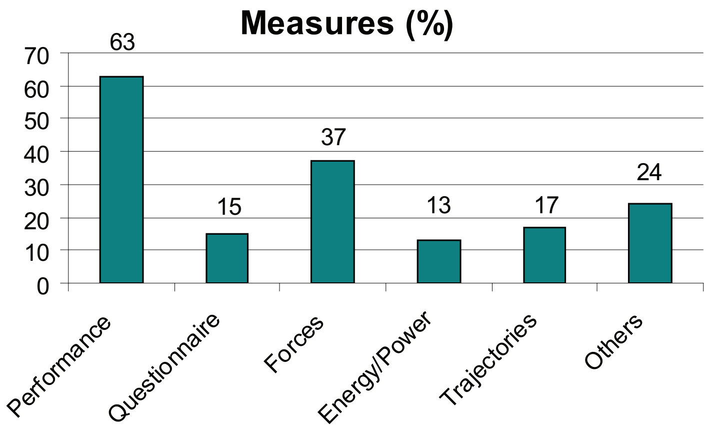


Figure 3.3: Measures involved in the analysis of experiments on haptic collaboration reported in Appendix B. If several measures were used in one study, they are counted additional. The percentages reported here are calculated in relation to the absolute amount of 54 independent studies.

and online with behavioral measures, which is of high interest for the development of artificial partners as it is more cloesly linked to the design of models for robots. Only half of the conducted studies measure forces or power/energy (37% + 13% = 50%, both requiring force measures). This percentage is lower than expected in research on haptic collaboration, where the exchange of force signals is assumed to be a key-component in the communication with a partner. Only few experiments (17%) analyze (position, velocity or force) trajectories over time to understand the actual behavior in haptic collaboration. This analysis of trajectories is done by inspection, a valuable tool to find qualitative differences in behavior. However, to gain knowledge for the design of technical collaboration partners, more quantitative descriptions have to be involved in future studies as it is hard to derive design guidelines for parameters in the control architecture of artificial partners on the basis of qualitative statements. Keeping the goal to develop technical partners which understand human behavior in mind, it is surprising, that most studies measure performance based on position signals, but not force related measures. The latter measures allow describing the collaborative behavior itself, in contrast to its results. However, these findings can be explained by the high amount of evaluation studies in this state of the art, which do not focus on the understanding of behavior. Depending on the specific research interest, several more specialized measures such as, lifting altitude of the object [Evrard and Kheddar, 2009], or success rates in dancing steps [Takeda et al., 2007a] are used in 24% of the investigated experiments. The majority of those measures can be interpreted task-dependent only. Thus, they are of importance in the evaluation of specific scenarios, rather than for gaining fundamental knowledge on haptic collaboration.

3.4 Interaction Types and Collaboration Levels

When conducting experiments to evaluate robotic partners for haptic collaborations or to find generic principles of human behavior in this context, interaction between partners, whether human-human or human-robot, is per definition part of the experimental design. This section

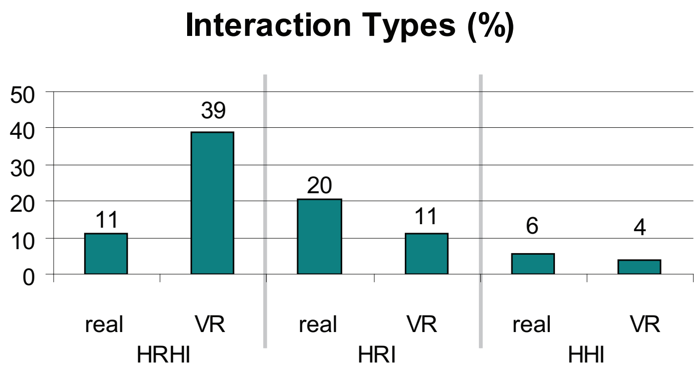


Figure 3.4: Overview on used interaction types as part of the experimental design in studies reported in Appendix B. HRI refers to human-robot interaction; HRHI refers to robot-mediated human-human interaction. HHI describes human-human interaction which is not technically mediated. Within these categories natural visual feedback is distinguished from virtual reality.

investigates the interaction types used in the experimental setups in the 54 studies reported in Appendix B.

The more standardized an experiment, meaning high control on the presented conditions, the more precise is the statement on causality between the controlled variations in the experimental conditions and the resulting measurements (internal validity). The drawback of such highly standardized experiments is that they do not necessarily represent real applications, leading to a lack of external validity. In contrast, the high complexity in real applications can easily lead to a high amount of data, especially noisy data, which are difficult to analyze and draw conclusions on. Thus, an important decision when designing experiments in the context of haptic collaboration has to be taken on the validity focus. In the majority of cases there is a trade-off between both types of validity. Hence, an experiment can either focus on the identification of causal rules *or* the examination of real applications.

Interaction Types: One component, which has to be taken into account when considering the validity of results, is the constellation of collaboration partners in a given experiment: The advantage in investigating *two human partners (HHI)* is that found results will represent natural human behavior. This is of importance when following the user-centered design approach to substitute one out of two human partners by a robot, based on models gained in the first step. This constellation is of high interest when collecting basic knowledge, which can then be transferred to the design of technical partners. Within the investigated studies 12% analyze human-human behavior. The need to measure performance and forces is challenging within natural (meaning non-mediated) interaction between two users, which may explain the low number of studies with this interaction type. However, the focus on two interacting humans reveals the agreement of the research community towards a user-centered design approach when developing robotic partners. To enhance behavior measurement, *technically mediated setups to investigate two collaborating humans (HRHI)* are required. In addition, haptic interaction in virtual realities or multi-user tele-present scenarios use this setup. Hence, this is the approach chosen by most experiments (50%) conducted in haptic collaboration. Thus, the experiments allow for a controlled manipulation of the connection between partners. Last, *existing technical partners and humans (HRI)* can collaborate. This constellation enables to study the reaction of human users to partners showing standardized or non-human-like behavior. It is the chosen approach in 31% of the experiments discussed here. It is assumed, that the number of studies addressing this interaction type increases in line with advanced knowledge in the filed of haptic collaboration: For now, the knowledge of haptic collaboration is not profound enough allowing for a high number of autonomously acting robots. Figure 3.4 illustrates the frequencies in which interaction types of collaborating partners are addressed in the state of the art. Here, it is further distinguished how the visual feedback in the given experiment is provided, contrasting real feedback or virtual feedback (including all artificial visual information from e.g. computer monitors). Technical mediated visual feedback is another possibility to control the perceived signals of the human user within an experimental setup.

Collaboration Levels: Within the conceptual framework described in Chapter 2, *two levels* of haptic collaboration based on the task complexity can be distinguished. The lower level deals only with the shared action plans of the two partners how to move the jointly manipulated object, i.e. *how* to combine the two individual force applied on the object. In addition, high-level haptic collaboration requires shared decisions on *where* to move the object (along which trajectory). The studies reported in Appendix B are classified within this framework. The classification criterion by the description of the two levels is not totally distinct. Here, the level of each experiment is decided in relation to amount of possibilities for goal-directed object trajectories in the given task, i.e. if shared decision making on the object trajectory is required. This separation allows describing a general trend in this overview on haptic collaboration experiments: 70% of the experiments involve designs and setups which imply low-level haptic collaboration (low complexity) and only 30% deal with more complex scenarios. This finding is related to the recency of the research field. Once the underlying rules and key-factors in low-level haptic collaboration are understood, experimental setups more linked to real life applications, i.e. higher complexity, can be employed.

3.5 Participants and Statistical Analysis

In the given context, the goal of psychological experiments is to understand aspects of human behavior and information processing in order to derive design guidelines for robotic architectures and associated signal flows. In haptic collaboration research, this implies to describe typical, interactive behavior. To derive these general statements, a representative sample out of a theoretical user population is a key-requirement. Herein we differentiate between content representativity, i.e. if the participants are typical for the population and statistical representativity. Here, it is intuitively accessible that results based on a small group are less reliable than those based on larger samples. As a rule of thumb, representativity is given, when each cell in the experimental plan (related to the experimental conditions) contains a minimum of 10 units of analysis, e.g. Richter and Fl?ckiger [2010]. The recommended overall sample size depends on several factors: a) the experimental design (e.g. whether it is a between-subject design, where each cell of the experimental plan contains different units, or a repeated-measurement design, where the same units are tested under the different conditions; or the expected effect

size); b) the goal of the study, i.e. if it is an exploratory study (which requires less participants) or a hypothesis-testing study (which involves more participants); c) for hypothesis testing: the recommended sample size depends on the yielded experimental power (related to the expected effect size, and thus, requires pre-knowledge), and the significance level. For a calculation of the required sample size it can be referred to e.g. Cohen [1977]. The degrees of freedom in human behavior are immense. Thus, if studies are conducted as case studies based on only one or two participants, it is questionable if a typical behavior in haptic collaboration is shown, which can be generalized to a broader population. Hence, the danger of spuriously found effects in measurements is high. The reason for talking about *units of analysis* instead of *participants* in the context of haptic collaboration research is the following: One assumption of inference statistic tests is that the tested values are *independent*. When studying any kind of interaction, this independence can not be assured due to a possible adaptation to the partner. This holds true especially for haptic interaction where the partners are coupled through a (rigid) connection. There are several possibilities to deal with this challenge:
1) The experiment is designed such that one participant only interacts with *one* other partner. Thus, the dyads taking part in the experiment are independent (contrasting the studies where all participants interact in all possible dyad combinations). Then, the *dyad is the unit of analysis* and independence of measures is achieved. Still, individuals within an interacting dyad cannot be analyzed this way.
2) Another approach which aims to examine individual behavior is to have an *standardized* partner, who is interacting with participants. This way, one partner is assumed to show identical behavior, i.e. not influencing the experiment or all participants in the same way. Only the second partner, the *one participant, is the unit of analysis*. This can be realized in two manners: a) HRI, the robot can be programmed to perform exactly the same actions in each interaction; b) HHI or HRHI, where a confederate of the experimenter team tries to act in a standardized way interacting with participants. The drawback of this procedure is that collaboration involves adaptation towards the partner. However, the trained partner cannot adapt naturally to the partner as his/her aim is to present a standardized partner. In the author's opinion this is contradictory to the goal of studying collaboration.
3) A third possibility to deal with the question of how to examine the effect of the interaction partner is to directly address it by *modeling the interdependencies*. This can be done by using an experimental design which allows participants to interact with several partners (e.g. round robin design [Kenny et al., 2006]) and use more advanced methods such as hierarchical modeling (compare e.g. Fitzmaurice et al. [2004]; Gelman and Hill [2008]) for analysis. The disadvantage of this approach is that the dyadic data is no longer independent and cannot be investigated additionally with standard methods .

Participants: The number of participants involved in the state-of-the-art experiments is reported in Figure 3.5. Only 41% of publications involve more than the recommended minimum of ten units of analysis. In contrast, 26% of the experiments are executed with less than five participants. Even though results in those studies are often interpreted as general statements, their generalizability towards the population of users is questionable.

Analysis: In the context of the generalizability of found results, it is also of interest how

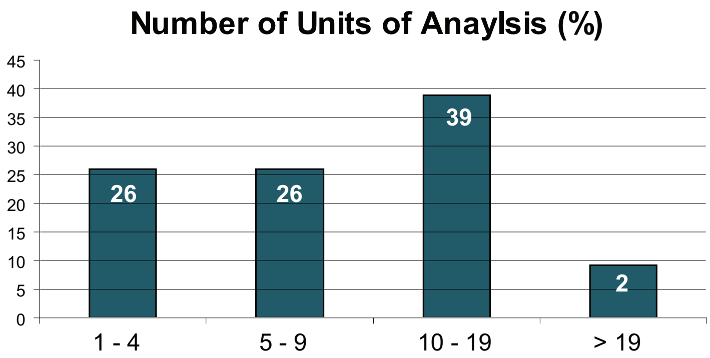


Figure 3.5: Number of units of analysis in the experimental studies on haptic collaboration reported in Appendix B. Units of analysis which can be *dyads* if both partners are participants or *individuals* if one partner is a standardized partner. If more than one experiment is conducted in one publication, the mean number of units of analysis is reported. One study reported only to have "several" participants involved [Kosuge and Kazamura, 1997], which is interpreted as a number between five and nine. If all dyad combinations within a given group of participants are tested, we report the number of participants, not the dyads.

the data is analyzed. Inference statistic tests lead beyond descriptive statistics, which describe a given data set by reducing the data to some parameters (typically mean and standard deviation). Inference statistic techniques inform on the representativity of results under a given confidence level. In the state of the art only 39% of the studies are analyzed with inference statistic methods, 33% report descriptive results. Thus, it is not investigated whether found differences between the experimental conditions are due to noise (as inter- or intrapersonal differences) or if a significant effect is found. Note, that the significance of an effect does not only depend on its actual size and the amount of noise, but in addition on the number of participants (via the standard error, see e.g. Field [2009]; Howell [2007] for more information).

3.6 Related Experimental Studies

While literature on experiments in haptic collaboration was examined so far, this section gives a brief summary on related experiments, which do not directly address the research field. Those studies are of high importance to gain a full picture of haptic collaboration and to design future experiments. This following list is not complete and serves as on overview only:

- Studies (psychophysical) on the perception of haptic signals and execution of kinesthetic tasks, by individuals e.g. [Groten et al., 2008; Pongrac et al., 2006] and between persons e.g. [Shergill et al., 2003].
- Studies which address non-human-like assistance functions, e.g. [Bayart et al., 2005; Morris et al., 2007; U. Unterhinninghofen, 2008].
- Experiments which focus on jointly executed haptic tasks which require sequential

interaction between participants, contrasting parallel actions on the manipulated object or interaction point, e.g. [Giannopoulos et al., 2008; Knoblich and Jordan, 2003; Meulenbroek et al., 2007; Sebanz et al., 2003a,b].

- Experiments investigating the affordance to collaborate by physiological variables, e.g. arm-span [Isenhower et al., 2010; Richardson et al., 2007].
- Studies addressing "haptic communication´´ based on newly-learned signals, e.g. haptic gestures [Oakley et al., 2001], tactile signals [Chang et al., 2002], haptic icons [MacLean and Enriquez, 2003], via foot-devices [Rovers and van Essen, 2006] or via hand-held device [Fogg et al., 1998].
- Experiments dealing with the short-timed haptic interaction when passing objects, e.g. [Sallnäs and Zhai, 2003].
- Studies on interaction in kinesthetic tasks where no haptic feedback is given, e.g. [Groten et al., 2007, 2009c; Heldal et al., 2005; Ruddle et al., 2002, 2003; Smith et al., 1998].

3.7 Conclusion

For the first time this chapter has provided an overview on how research in haptic collaboration is conducted with psychological experiments to date, referring to the overview-table on experiments in Appendix B. The discussion revealed the increasing interest in haptic collaboration research during the last 15 years. However, it was found that experimental research in haptic collaboration is still in its beginnings. The research interests and the related measurements above all focus on performance and evaluation studies. Even though the exchange of forces is essential in haptic collaboration, only half of the reported experiments measure those. Modeling attempts of human behavior are rare. Thus, little is known about underlying mechanisms of how humans conduct haptic collaboration tasks. This may not only be explained by the short existence of this research field, but additionally by challenges related to interdisciplinary work.

Together with Appendix B this chapter provides an overview on already conducted studies, which can enhance the design of those future experiments by hinting open research questions. In addition, this chapter clearly states the need for further experiments on haptic collaboration.

Based on the overview on state-of-the-art experiments and the related discussion on trends presented in this chapter, the next chapter will introduce methods to conduct new experiments: Experimental designs and corresponding measurements are described in detail.

4 Research Interest, Experimental Paradigm and Measures

Whereas the last two chapters provided a theoretical background to conduct research in haptic collaboration, the current chapter will introduce an experimental paradigm and behavioral measures, which are required to find new experimentally gained insights into this topic. This chapter is divided into three subchapters. The first one presents the two main research interests addressed via experiments in this thesis. These interests influenced the decisions on the experimental paradigm and the measures presented in the following two subchapters. However, it is the major goal of this chapter to present both the experimental designs and the measures in general terms. This way, future research can profit by using the same designs and measures with different research questions. The argumentation in favor of variations in design and measures are precise enough to enrich related decisions future work. The experimental paradigm introduced in the second subchapter allows a manipulation of the jointly desired object trajectory, representing the shared action plan. The two different levels proposed in the haptic collaboration framework can be studied iteratively by two different experimental designs. Next, the subchapter on measures provides an overview on force and energy components of relevance in haptic collaboration, which so far has not been reported in literature. Then, an efficiency measure is provided which allows one to relate task performance to the physical effort required to achieve it. Until now, the latter component has been neglected in haptic collaboration research. Even though dominance measures exist in literature, they have not been compared profoundly. In addition, a new measure called cognitive dominance is proposed. The experimental designs and measures presented are the basis of the results reported in the remainder of this thesis.

4.1 General Research Questions

Next to the theoretical background given by the framework (Chapter 2) and the discussion of the state of the art on haptic collaboration research (Chapter 3), this dissertation provides experimental results on two research interests, which are outlined in the following:

4.1.1 Intention Negotiation

One fundamental question, which should be answered before the challenges of developing behavior models in the context of haptic collaboration, is whether “haptic communication” exists. If the integration of two human partners‘intentions, possibly including a negotiation of individually different intentions, cannot be executed via this channel, it is not necessarily required that technical partners show an corresponding behavior. So far, no studies have investigated systematically if intention integration in haptic collaboration tasks is actually enhanced by additional information exchange via force and position signals between human partners [1]. In this thesis, task performance as an indicator of successful collaboration is related to physical effort as a measure of the negotiation costs. The relation between these two measures is called efficiency. The following subchapters will introduce the experimental designs and measures to address this research interest.

It is possible not to provide haptic feedback at all in virtual scenarios. Artificial forms of haptic feedback, contrasting the feedback resulting from human-like behavior in haptic collaboration, can be implemented in robotic assistant partners (as passive following). To show the potential benefit in deriving models dealing with the challenges of implementing human-like behavior in haptic collaboration, efficiency of haptic collaboration between humans is experimentally addressed. Herein, it is the goal to identify important factors, which can affect efficiency in haptic collaboration. Relating to the research overview on existing experiments in Chapter 3 the following factors are addressed: a) the effect of a partner by introducing experimental conditions, where the task is executed by a single user and b) the effect of mutual haptic feedback between partners by introducing a control condition without such feedback. Furthermore, efficiency will be studied for each level of haptic collaboration separately (compare Chapter 2) to derive insights into an effect of the need to negotiate intentions. The results of the related experiments are then presented in Chapter 5.

4.1.2 Dominance

Each of the collaborating partners in jointly executed haptic tasks is only partly responsible for the resulting behavior of the overall system, and thus, contributes only partly to the joint task performance. A key-concept in haptic collaboration are shared actions, which are based on individual intentions. The challenge lies in modeling of the robotic partner to behave human-like when executing such shared actions. Here, it is not enough to have a model, which performs well in a given task that is executed individually. The collaboration with a partner has to be considered explicitly in the integration of individual action plans. Intention integration should be possible in an intuitive manner to gain high performance and user-friendly interactions. By investigating the dominance distribution between two human partners, it is possible to gain information on roles of humans in haptic collaboration when sharing the responsibility of a task outcome. The identification of such dominance roles enables precise quantitative guidelines for robotic partners.

The influence of mutual haptic feedback will be analyzed by employing a control condition without such feedback [2]. Again, the need to negotiate intentions is experimentally manipulated by conducting two different experimental studies for the two levels of haptic collaboration as introduced in Chapter 2. The results and related guidelines for robotic partners, are presented in Chapter 6.

[1] except for the studies by the author of this thesis related to in Chapter 5
[2] In the dominance context the effect of a partner is not investigated as this measure requires two inputs

4.2 Experimental Design

In order to address the research questions raised above, associated experiments are described in the following. The experiments separately address the two haptic collaboration levels proposed in the conceptual framework. The focus is on two general concepts: *efficiency* of intention integration via mutual haptic feedback and *dominance* difference in the collaborating partners' behavior.

Haptic collaboration is no well-studied subject yet as elaborated in Chapter 3. Hence, there is only little theoretical knowledge available. Therefore, it is decided against experiments in complex setups of real applications. High complexity would have led to a high amount of interdependent, multi-dimensional data. Without pre-knowledge on what to look for in this data, experiments in real-life scenarios do not seem promising to find fundamental insights into haptic collaboration. Drawback of the decision in favor for fundamental, structured experiments is that the generalizability to real applications is not necessarily given and has to be proofed in additional experiments. However, standardized experiments lead to higher internal validity. The reduction of the complexity is desired for both collaboration levels. For these reasons, the experiments in this thesis are based on a jointly executed tracking task where two persons manipulate a virtual object together. In line with the general approach in this thesis, the experiments presented in the following are conducted with human dyads to gain knowledge about "natural" human behavior in haptic collaboration. In contrast to existing experiments in this context, the new designs and setups offer the following advantages:

- The latent concept of the individually desired trajectory is made measurable and experimentally controllable.

- For the first time, it is possible to investigate shared decision making via mutual haptic feedback.

- An experimental manipulation of the need to negotiate intentions between partners is realized.

Furthermore, the experiments allow the introduction of control conditions without mutual haptic feedback in order to understand the effect of this feedback. In addition, the setup enables exact measurements of position and force signals. The two presented experimental designs address the two levels of haptic collaboration presented in the framework (Chapter 2) iteratively as a first attempt to investigate the proposed components separately and allow a first validation of the framework.

Components of the experimental setup and design are described in detail in the following.

4.2.1 Jointly Executed Tracking Task

The tasks mostly used in existing experiments on haptic collaboration are pointing or positioning tasks (e.g. Mateo et al. [2005]; Rahman et al. [2002b]; Reed and Peshkin [2008]), tracking tasks (e.g. Basdogan et al. [2000]; Glynn et al. [2001]; Glynn and Henning [2000]), and cube manipulation/lifting of an object (e.g. Evrard and Kheddar [2009]; Hamza-Lup et al. [2009];

Sallnäs et al. [2000]; Sallnäs [2001]). Mostly one-dimensional tasks are chosen to reduce complexity. Here, a jointly executed tracking task as a structured experiment representing real scenarios based on haptic collaboration is chosen for the following reasons:
A) As stated in Chapter 2, intention integration is assumed to be a key-concept in haptic collaboration. Intentions can only be addressed in an experiment where the individual and (resulting) shared intentions, i.e. the desired behavior, are not only cognitive representations, but are made explicit in the experimental design. In a one DoF pointing task only the final position is clearly defined and the movement trajectory in time is not experimentally controlled. In contrast, the joint tracking task paradigm allows instructing the desired behavior/goal at each time point.
B) A virtual task, in contrast to a task taking place in reality (compare e.g. Reed and Peshkin [2008]), is chosen because virtual reality offers the advantage of controlled manipulation of the visual information of the track, resembling the individual action goals. Thus, the visual feedback given can be experimentally controlled and reduced to enhance a focus on the haptic modality in a first step. In particular, this setup allows studying high-level haptic collaboration by introducing different individually preferred action plans. Thus, shared decision making in accordance with the described framework (see Chapter 2) can be investigated.
C) When studying the effects of a partner and mutual haptic feedback it is required that adequate control conditions can be realized within the experimental design. The virtual tracking task paradigm allows to be executed by one person only (controlling the effect of a partner) and to be executed without haptic feedback from the partner (addressing the effect of haptic interaction).
D) The joint tracking task paradigm enables the implementation with several devices and in virtual realities of varying complexity (e.g. visual information, degrees of freedom, dynamics of manipulated object). Thus, once generic models are found and key parameters in a scenario of low complexity are identified, the generalizability of these results can easily be tested.
E) The tracking paradigm is well studied for individual performers (e.g. Jagacinski and Flach [2003]; McRuer and Jex [1967]; Rasmussen [1983]; Wickens [2004]) and thus, there are descriptive and control theoretic models provided for the single person behavior, which may be adoptable for two persons, see Feth et al. [2009a] and compare Section 2.1.7.
F) As Rasmussen [1983] points out, the tracking task is non-challenging when it is operated by a single individual and is therefore handled on the skill-based level. Hence, when participants are asked to execute a tracking task collaboratively, it is ensured that enough higher cognitive resources are still available to focus on the collaboration with the partner.

To the author's best knowledge, this experimental task has so far only been used on lower level haptic collaboration, i.e. with identical reference paths for both parters, by Basdogan et al. [2000]; Glynn et al. [2001]. The here introduced shared decision making in a tracking task, i.e. different reference paths for the partners as part of high-level collaboration, has not been investigated so far in literature.

4.2.2 Two Levels of Haptic Collaboration

To gain insights into the two different levels of haptic collaboration, the meaning of the decision module introduced in Chapter 2 is taken literally. In accordance with the low-complexity approach, binary decision making is represented by the higher level haptic collaboration within the joint tracking task paradigm. In Figure 4.1 the relation between the experimental design and real life applications (table carrying) is demonstrated together with the substitution of one partner

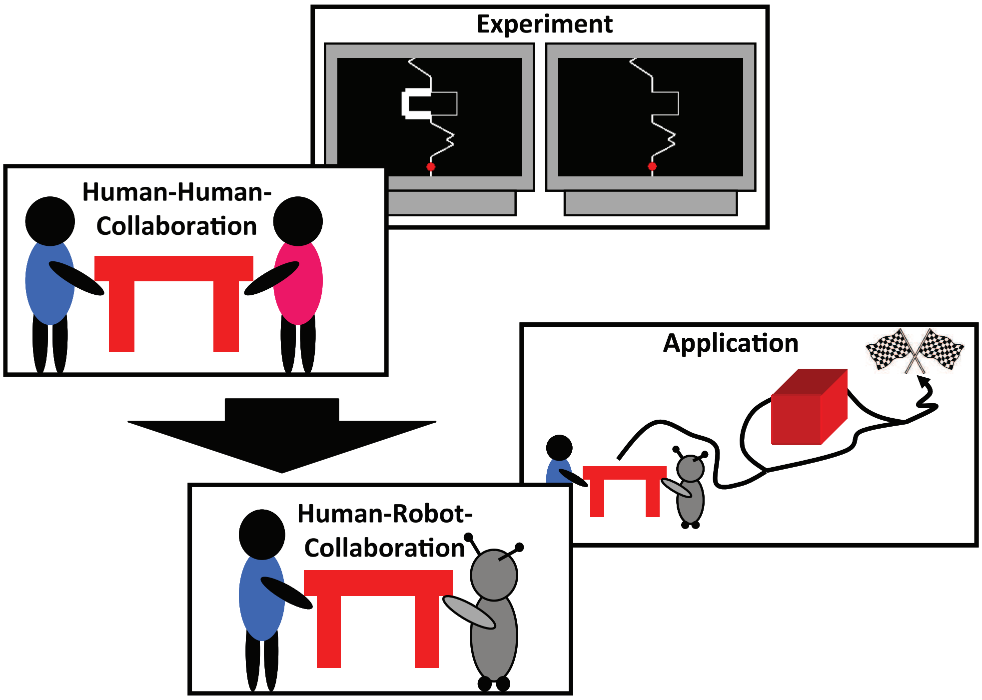


Figure 4.1: One approach to design intuitive technical partners in kinesthetic tasks is to substitute one human partner of the interacting dyad. The knowledge gained on HHC in controlled experiments can enhance HRC in actual applications.

(towards real human-robot collaboration, here on high-level collaboration). However, it should again be noted that both haptic collaboration levels address basic concepts of haptic collaboration; the joint tracking task is not supposed to meet the complexity of a real life scenario.

4.2.3 Control Conditions

For a deeper understanding of haptic collaboration, control conditions have been introduced in literature which allow the investigation of the effect of a partner and haptic feedback on various measures. By eliminating either one of the two key parameters in haptic collaboration, the advantages of haptic collaboration can be addressed. In the existing literature, conditions without collaboration, i.e. without a partner (compare e.g. Reed and Peshkin [2008]) or without haptic feedback are introduced (compare e.g. Basdogan et al. [2000]; Sallnäs et al. [2000]; Sallnäs [2001]). Depending on these control conditions, the conclusions, which can be drawn from differences between the experimental conditions, vary. In the following, an overview on (dis-)advantages of possible control conditions is presented:

A) *Single-person, single-hand control condition:* In this condition, interaction does not take place by definition. Mental models of the partner and action plan integration are not necessary. Hence, differences between the single-person condition and the haptic interaction condition can have several reasons, i.e. the effect of the haptic feedback, the increased workload due to action plan integration, the task simplification due to the support of the partner, and possible social effects (to name some sources of variations in measurements) are confounded.

B) *Single-person, dual-hand condition:* This control condition does not require mental models of a partner but still interaction takes place due to the fact that the two hands have to be coordinated. The dual-hand condition can be presented with and without haptic feedback, and thus, allows to study the effect of feedback separately from the effect of interaction in motor-coordination. The effect of shared mental models can be examined. The challenge lies in the fact that the single person has only one dominant hand, whereas the partners in a dyad can both work with their dominant hands. Therefore, the comparability of task execution between those two conditions is not fully given.

C) *Without-haptic-feedback control condition:* Here, interaction takes place as in the haptic condition on the physical coordination level as well as on the cognitive level, because mental models of the partner are required. However, providing visual feedback from the partners actions only, potentially leads to inconsistencies when two persons jointly manipulate an object. For the individual the proprioceptive movement of the muscles and the so-estimated object movement is not necessarily consistent with the real object movement, which is also influenced by the partner. Therefore, this control condition confounds the effect of additional haptic information from the partner with effects due to disturbances related to this feedback. In addition, two cases have to be separated: a) the haptic feedback of the object is still provided in this control condition as in the here presented experiments or b) no haptic feedback at all is given (e.g. Basdogan et al. [2000]; Sallnäs et al. [2000]). In the latter case, the overall effect of haptic feedback cannot be separated from the effect of haptic feedback on the actual interaction, thus communication between partners. In relation to the general research interests in Section 4.1, haptic feedback from the object is provided in the control condition. This seems to be the best solution in the given context as further discussed in Section 5.1.

D) *Technical partner:* Comparing a technical partner to a human partner is foremost done to evaluate a model of an interactive haptic partner. Differences between the two conditions allow defining the quality of such a model. Because the model needs to be defined beforehand, this control condition is added for the sake of completeness but its use depends on the development of advanced technical partners.

In the experiments described in the following, control condition **A and B** are chosen to study low-level haptic collaboration. To the author's best knowledge no studies, other than the one presented here, have so far used conditions without haptic feedback (control condition A) and a partner (control condition B) within the same experiment. For higher level haptic collaboration involving shared decision making, the single-person control condition is of no use as shared decision making can only be studied within dyads.

4.2.4 Experimental Setup

After the presentation of the task and the experimental conditions in the last section, the specific realization of the experiments on low- and high-level haptic collaboration are shown in the following. First, the general design of the experiments and their setup is described for lower level haptic collaboration. Then, the undertaken extensions in order to address high-level haptic collaboration are introduced.

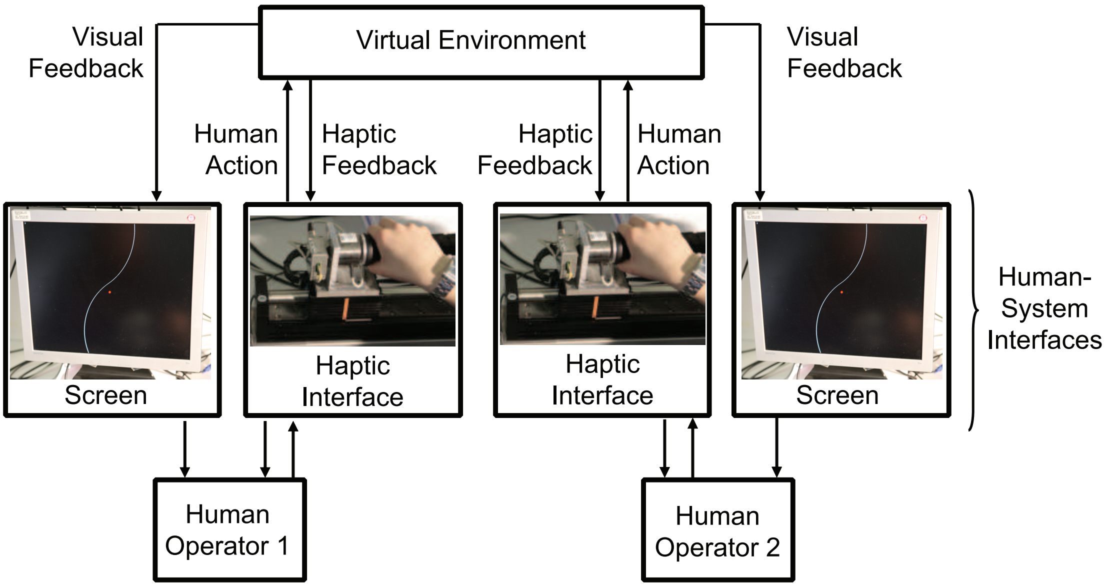


Figure 4.2: Experimental setup where two users can jointly manipulated a virtual object. Except for the visual task instruction, the setup is identical for the experiments in low- and high-level collaboration. The figure shows the signal flow between the two operators and the virtual environment.

Low-Level Haptic Collaboration

The general design of the setup to study virtual haptic collaboration between two human users is depicted in Figure 4.2. A description of the underlying control of the haptic devices is given in Appendix C. To match the definitions of low-level haptic collaboration within the conceptual framework introduced in Chapter 2, the experiment conducted to study this level was designed in the following way:

Participants are asked to move a virtual object, visually presented by a cursor (red ball) along a given reference path (see Figure 4.3). As introduced in more detail below, four different conditions, two single person and two interaction conditions (two partners), are defined. All four conditions have in common that the reference path is designed as a random sequence of the same components (triangles, curves, straight lines, jumps). It is displayed as a white line on two black screens (both showing the same scene). As the path scrolls down the screen along the *y-axis* with a constant velocity of 15 mm/s, participants are asked to track it as accurately as possible. The overall path length is constant for all trials and experimental conditions. One trial takes 161 s. The horizontal position of the red ball renders the resultant position of the haptic interfaces the participants use to interact with each other. These haptic interfaces have one degree of freedom (1 DOF) and allow movements along the *x-axis* (traversal plane of operator). Each interface is equipped with a force sensor (burster load cell 8542-E), a hand knob and a linear actuator (Thrusttube). Their control is implemented in Matlab/Simulink and executed on a PC running the Linux Real Time Application Interface (RTAI). The sampling rate was 1kHz. The graphical representation of the path is rendered on another computer; communication between both PCs is realized by an UDP connection in a local area network. Hence, negligible time delay can be assumed.

The control of the haptic interfaces is designed to model a jointly carried virtual object. The

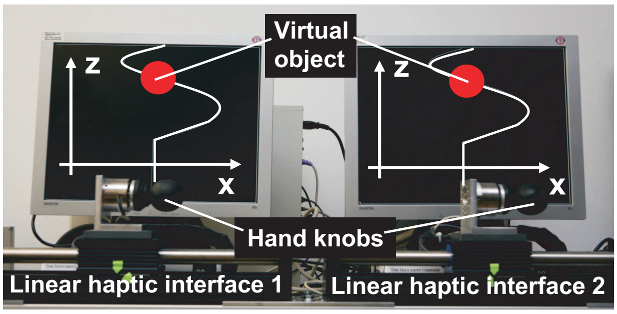


Figure 4.3: Photo of the experimental setup consisting of two linear haptic interfaces and two screens with the graphical representation of the tracking path. During experiments a wall was placed between the participants blocking the view on the other participant's screen.

virtual object is defined to be a pure inertia, which can be by the differential equation:

$$f_{sum}(t) = f_1(t) + f_2(t) = m\ddot{x}_o(t) \tag{4.1}$$

where f_{sum} is the sum of the forces applied by the participant/s, m is the virtual inertia and $\ddot{x}_o$ is the acceleration of the virtual object and, hence, of the haptic interfaces. The corresponding transfer function in the Laplace domain

$$G_o(s) = \frac{X_o(s)}{F_{sum}(s)} = \frac{1}{ms^2} \tag{4.2}$$

is realized by a position-based admittance control (for more details refer to Feth et al. [2009b]). This setup allows not only the measurement of the resulting force $f_{sum}(t)$ but also of the individual forces $f_1(t)$ and $f_2(t)$ applied by each participants as would be the case in real object manipulation.

In order to investigate the effect of *haptic collaboration* in the joint pursuit tracking task, a condition with mutual haptic feedback between partners and three different control conditions are examined. The resulting four conditions are described below:

1) *Vision-haptic condition (VH)*: The partners receive visual feedback of the virtual object, which they jointly manipulate. In addition, they are connected via the haptic channel. Next to the inertial forces of the virtual object (m=20 kg), they can feel the forces applied to the object *by their partner*. This is achieved by introducing a virtual rigid [3] connection between the interacting partners. Thus, $x_o(t) = x_1(t) = x_2(t)$ and the virtual object (cursor) position is determined by transforming Equation (4.2) to the time-domain and solving it for $x_o(t)$

$$x_o(t) = f_{sum}(t) * g_o(t) \tag{4.3}$$

with $g_o(t)$ is the inverse Laplace transform of $G_o(s)$.

2) *Vision condition (V)*: Again, visual feedback is provided. The inertia ($m = 20$ kg) of the cursor is divided into two parts, such that each partner has to move 10 kg, which presents an equal sharing of the workload. The participants feel only the inertia, but not the forces applied by their partner. This contrasts with haptic interaction studies in the literature where no haptic

[3] realized with a high gain PD-controller, compare Appendix C

feedback at all is provided in the interactive control condition. In contrast, environmental force feedback from the object (mass) is provided in all conditions. Thus, solely the effect of the haptic feedback *between* partners can be investigated. The cursor position is defined as the mean of the two individual device positions. Therefore, each partner can only infer what the other is doing from inconsistencies between his or her own movements and the resulting cursor position (for further research on inconsistencies in this context see Groten et al. [2009c]). Here, the object position is calculated by

$$x_o(t) = (x_1(t) + x_2(t))/2. \tag{4.4}$$

3) *"Alone" condition with full interial mass (AF)*: The participant executes the task alone. He/she has to move the virtual inertia in the same way as two participants do in the VH trials ($m = 20$ kg).
4) *"Alone" condition with half intertial mass (AH)*: The participant executes the task alone. He/she has to move only a $m = 10$ kg inertia, which is identical to the workload of an individual in an interaction task with equally shared workload or the workload in the vision condition.

Participants are not allowed to speak to each other during the experiment. In this way, it is guaranteed that only haptic communication is studied. They are informed about each condition beforehand. In addition, they know that the first curve of the tracking path is for practice and will be excluded from the analysis.

The sequence in which the conditions are presented to the participants is randomized. For a further standardization of the test situation the following arrangements are made: a wall is placed between the two participants to block visual information about the movements of their partner; participants use their right hand to perform the task (all of the participants are right-handed); white noise was played on headphones worn by the participants, so the noise of the moving haptic interfaces would not distract and verbal communication cannot take place. Further, the position (left or right seat) was randomized with the order of experimental condition. The task is considered intuitive enough to neglect a possible effect of pre-knowledge on haptic devices. To be sure to eliminate this factor, a repeated measurement design is chosen where conditions are counterbalanced.

High-Level Haptic Collaboration

The experiment developed to study high-level collaboration is designed employing shared decision making. Shared decision making is e.g. required when two persons carry an object and face the challenge how to surround an obstacle in their way, compare Figure 4.1. Except for this deviation from the setup described above, the two experiments are kept as similar as possible. However, on this level of haptic collaboration, no "alone" conditions are considered as the focus is on shared decision making which has no equivalent within one person. Thus, two different conditions regarding the feedback between partners are compared: The interactive condition with and without haptic feedback between partners.

Again, participants are asked to move a virtual inertia visually represented by a cursor along given reference paths. This time, the reference paths partly differ for the two partners and involve binary shared decision situations: Each participant sees a path on an individual screen and the cursor is again jointly controlled, see Figure 4.3. The velocity of 15 mm/s is kept constant

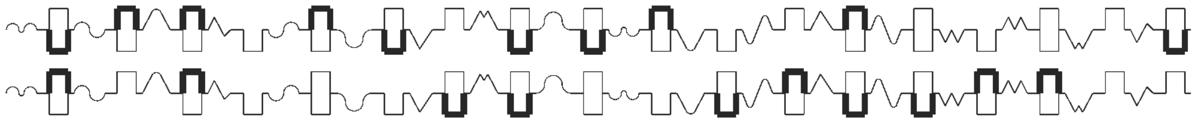


Figure 4.4: Exemplary path combination for binary decision making in the joint tracking task.

compared to the low-level experiment. One trial takes 190 s. The same interfaces are used. The dynamics of the virtual object are again defined by Equation (4.2).

To introduce *shared decision making* to the tracking task paradigm, it is necessary to fork the track to meet the requirement of available options when defining decisions. The track is forked with an angle of 180° between the two options leading to a rectangular path, which required clear decision statements. These decision situations offering two options are separated by intermediate no-decision track sections, see Figure 4.4. The track could be foreseen by 5s. All decision situations (defined as the 2s interval around the bifurcation of the track) are identical except for the instructed preferences explained below: They all require step responses of the cursor. Therefore, if the cursor is following the track accurately (possible only in theory), the task execution alone requires the same effort in all conditions. Differences in measures between decision types are therefore causally determined by the decision factor.

Part of the definition of shared decision making is intention recognition, or, in other words, the forming of mental models from the partner's preferences. When approaching the decision, participants do not know the partner's intentions in terms of the preferred path a priori. Thus, negotiation of the shared trajectory is required. However, there are two challenges in the experimental design of such situations:

A) the dyad could agree on one of the two options (either left or right track) at the beginning of the trial, stick with this solution and thus make no decisions in the remaining trials.

B) one of the partners could behave passively in decision situations - then the experiment would no longer address shared decision making.

To overcome these challenges, preferences are externally introduced to the decision situation. Hence, partners do not receive the same visual representation of the path. Although the general form is the same, the thickness in the analyzed decision types varied: A track segment can be depicted in normal path thickness or in forty times the normal path thickness. In Figure 4.4 one paired path is shown as an example. The variation of the path thickness introduces individual preferences into the tracking task because the path is easier to track when thicker. These preferences are equivalent to different information between partners in real scenarios. This leads to preferences in decision situations such as: a) one of the two tracks between which the decision had to be taken was thicker than the other, leading to a preference for the thicker path as it was easier to follow; b) only one path was depicted for an individual, thus no decision was possible but there was a clear preference for the depicted path. To make sure that the resulting step in the track presenting the latter situation was not associated with this situation only, the step was repeated in the track for both partners, so no decision had to be taken.

The preferences in these decision situations represent different information or possibilities for the partners in real life applications. As an example, one partner may be aware of different options to accomplish a task but prefers one of them due to easier task execution or is limited by his/her workspace. It is necessary that both partners communicate their preferences/recognize each others intentions to allow a smooth task execution and an overall high performance. To transfer this goal of high performance to our experiment, participants are instructed that their task was to reach the highest possible overall performance as dyad, not as individuals. Performance is defined as the deviation to the closer path of the two which was available for both partners (described in detail when reporting the experiments in Chapters 5 and 6). In order to strengthen this motivation, participants were informed beforehand that they would be paid performance-related. This, however, was not true; all participants gained the same amount of monetary reward.

Note, that this experimental design does not allow to study high-level haptic collaboration independent of the lower level. This is considered to be equivalent to real life applications and can be inferred directly from the structure of the conceptual framework introduced in Chapter 2. Next measures are introduced which allow an analysis of behavior in the presented experiments.

4.3 Measures

The last subchapter introduced the experimental design and setup developed in line with the research interests on intention integration and efficiency, as well as dominance in shared actions in haptic collaboration tasks. This section introduces measures, which enable a description of human behavior in these tasks, and thus, build the foundation for future modeling of technical partners.

As a first step, force and energy components, which are relevant in haptic collaboration, are presented and challenges involved in those measurements are discussed. Then, an efficiency measure is introduced that allows combining performance measures with physical effort measures such as forces and power. This efficiency measure is motivated by existing literature on haptic collaboration (summarized in Section 3), where experiments addressed performance-related measurements above all others, only 50% of the publications measured forces or power, and no studies (except for publications by the author of this thesis) combines these two most important behavioral measures in haptic collaboration. Therefore, only little is known about the relation between these two components. Next, dominance measures as a strategy to investigate action plans between partners are presented. Again, these measures are motivated by the interest in the research community as stated in Section 3. Within the dominance measure, two different components are differentiated: physical dominance and cognitive dominance, which is related to decision making processes. This division is in line with the two levels of haptic collaboration presented in the conceptual framework in Chapter 2.

It is important to note that this dissertation focuses on behavioral measures in contrast to subjective measures, which can be gained from questionnaires and in contrast to physiological measures. Here, behavioral measures are chosen because the overall goal is to achieve the same *behavior* for robotic partners compared to humans. Nevertheless, there is awareness that in later steps, especially in the evaluation of developed robotic partners, several measures should be combined to allow a full picture of haptic collaboration.

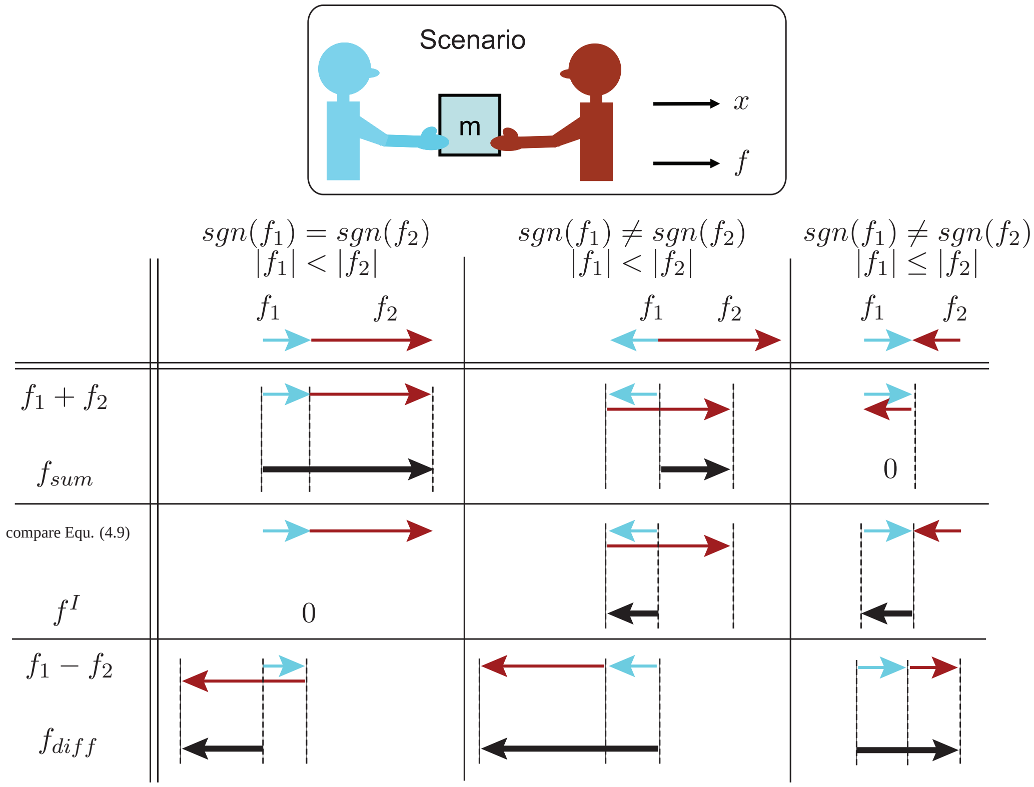


Figure 4.5: Comparison of the external, interactive and difference forces in three 1 DoF examples. The measure f_{diff} was introduced by Reed et al. [2005]

4.3.1 Force and Power Components

In Pan et al. [2005] a force decomposition of the applied forces by a human into *work* and *none-work* forces is given in the context of assistant robots. This decomposition is based on the fact that due to environmental constraints not all forces applied to an object lead to a movement of this object. In Pan et al. [2005] the vectors for *work* and *none-work* forces are defined to be independent (orthogonal), which can only be assumed with time-invariant constraints. In haptic collaboration, the constraints can be caused by the partner, who is applying forces in the opposite direction. Thus, the constraints are no longer time-invariant. Therefore, a different type of force decomposition is introduced here. In relation to the experimental setup described in Section 4.2, all of the relevant forces are restricted to a dyad manipulating a rigid object in a 1 DoF environment. However, the definitions can consistently be extended for more DoFs and more partners, as well as in direct haptic interaction without an object (e.g. guidance). The variables f_1 and f_2 [4] are the forces applied by each of the interaction partners on the object. Two different components of these forces are proposed in relation to Pan et al. [2005]: The external force f^E and the interactive force f^I. Thus, the force applied by partner 1 can be described as:

$$f_1 = f_1^E + f_1^I. \tag{4.5}$$

The movement of the object is caused by the sum of the external forces (related to *work*

[4]All measures derived in this sub-chapter can be defined for over time *(t)*. However, this is not explicitly mentioned in each equation.

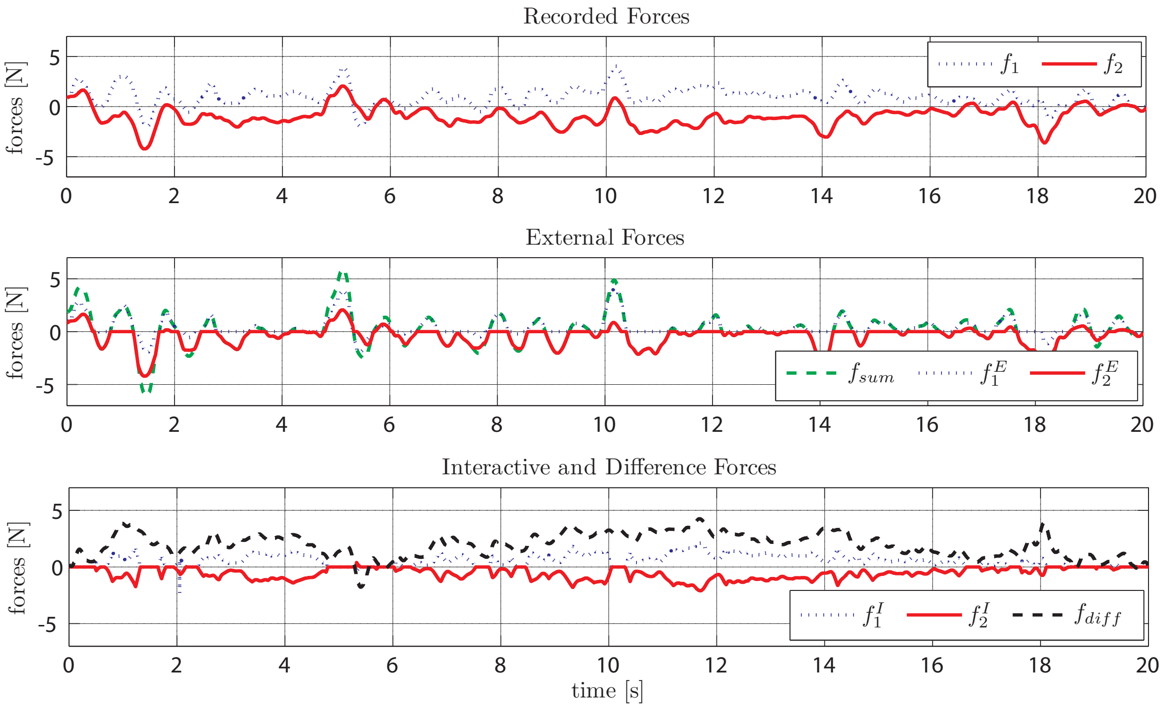


Figure 4.6: Measurements corresponding to all force types introduced so far are plotted over time for an exemplary trial in the joint tracking task experiment (low-level haptic collaboration, haptic feedback condition)

forces), which also equals the sum of f_1 and f_2

$$f_{sum} = f_1^E + f_2^E \tag{4.6}$$
$$= f_1 + f_2 \tag{4.7}$$

and, thus, implies

$$f_1^I \equiv -f_2^I. \tag{4.8}$$

Interactive forces occur if the two individuals do not apply forces in the same direction, but rather push against or pull away from each other (related to *none-work* forces). Thus, interactive forces are contradictory and do not contribute directly to task execution, i.e. do not lead to an acceleration of the object. Hence, interactive forces can be interpreted as wasted effort from a purely physical point of view. However, they could play an important role in communicative aspects of haptic collaboration. Interactive forces are defined to be non-zero only if the two partners apply forces in opposite directions. Furthermore, the absolute value of interaction forces is defined to be identical for both partners:

$$f_1^I = \begin{cases} 0 & \text{if } sgn(f_1) = sgn(f_2) \\ f_1 & \text{if } sgn(f_1) \neq sgn(f_2) \wedge |f_1| \leq |f_2| \\ -f_2 & \text{if } sgn(f_1) \neq sgn(f_2) \wedge |f_1| > |f_2|. \end{cases} \tag{4.9}$$

The interactive force of the other partner f_2^I is determined correspondingly by (4.8). Based on the obtained interactive forces, the external forces f_1^E and f_2^E are calculated by applying (4.5).

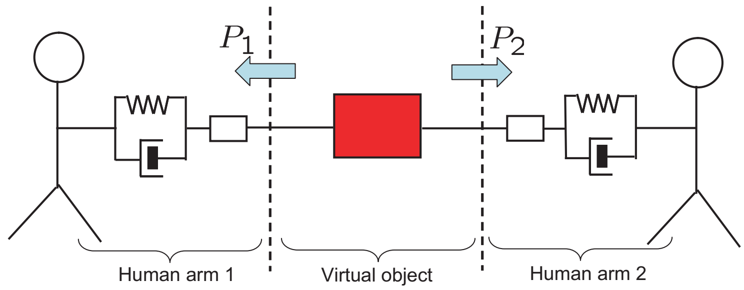


Figure 4.7: Energy flow in haptic human-human interaction, see also Feth et al. [2009b]

Figure 4.5 illustrates schematically interactive and external forces. Due to our definition of coordinate systems, partners push against each other if $f_1 > 0$ and pull away from each other if $f_1 < 0$.

In Reed et al. [2005] another form is chosen to describe the relation between two individual force inputs, the difference force, defined as:

$$f_{diff} = f_1 - f_2. \tag{4.10}$$

The difference forces are also displayed in Figure 4.5 to contrast them with the interactive forces defined above. The difference force has been claimed to be "a measure of disagreement of the members" (Reed et al. [2006]) that "has no effect on acceleration" (Reed et al. [2005]). The author of this dissertation does not agree with the latter statement as only f^I has no effect on the object movement. The measure f_{diff} is presented here to clearly contrast it with interactive forces. Figure 4.6 gives further explanations of the relation between the different force measures by plotting an exemplary measure over time.

The separation of internal and external forces has formally been proposed by Yoshikawa and Nagai [1991] in a different context. Note, that the definition of f^I as it is introduced here can be applied to translatory movements and is valid in static situations only: Forces measures due to the dynamics of the object or an active partner, who has to move the inertia of a passively behaving partner (the active partner has to move the passive partner's arm by the other partner in addition to the object) are not taken into account. Hence, these factors can be interpreted as error within the force measures. To the best knowledge of the author no dynamic definition could be derived in literature yet. At this early stage of haptic collaboration research the static definition is considered precise enough to investigate basic behavior patterns.

In addition to the force components, measurement of power allows characterizing behavior in haptic collaboration. Power-based measures combine the two aspects of haptic interaction signals: force and velocity. Corresponding, energy flows can be analyzed between the two partners:

$$P_1 = f_1 \dot{x}_1 \tag{4.11}$$

where P_1 is the **power / energy flow** from partner 1 to the environment (here including partner 2), f_1 is the force applied by partner 1 and $\dot{x}_1$ is the velocity of the object. The velocity is equivalent for both partners only when they hold on to the same interaction point. The energy

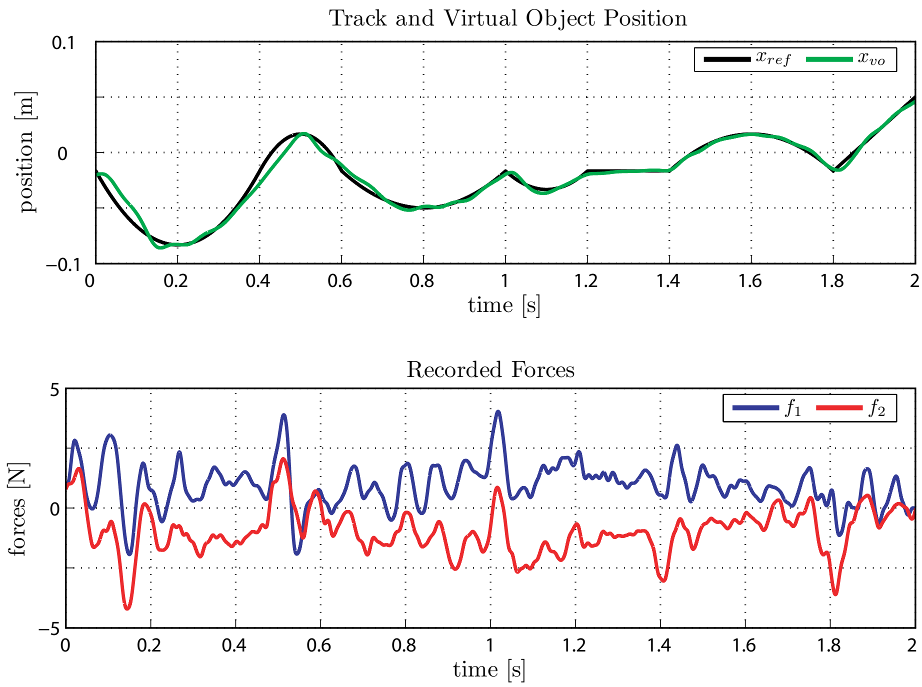


Figure 4.8: Exemplary measurement of position and force data in the joint tracking task experiment (low-level, haptic feedback condition). When both partners apply forces in the same direction (sign-wise) the measurements represent active manipulations of the object. This is not necessarily true for forces applied in opposite directions.

flow between partner 2 and the environment is defined correspondingly. The different systems, human operators and environment, and the respective energy flows are introduced in Figure 4.7.

After the force and power components have been introduced, specialties of behavioral measurements in haptic collaboration are addressed now:
1) Measurements in haptic collaboration are based on physical variables, which results in *time-series data* when collected. Specific information (parameters) has to be extracted to make interpretation possible. This can be done by methods, such as statistical analysis, time series analysis, or control-theoretic modeling.
2) It is important to differentiate between data representing interacting *individuals* and *dyads*. Depending on the analysis level, modeling assumptions have to be checked (i.e. two individual data streams within a dyad are not independent) and conclusions of data analysis have to be adapted to the level of the unit of analysis. The individual behavior within a dyad is the data most interesting to find hints for human-like models of technical partners. However, it is also the data most difficult to investigate as standard procedures of inference statistics cannot be applied, due to the dependent data. In methods for social psychology these problems are addressed, and the knowledge can be transferred to haptic collaboration research David A. Kenny [1996]; Griffin and Gonzalez [1995, 2003]; Kashy and Snyder [1995]; Kenny et al. [2001, 2006]; Maguire [1999]. Furthermore, to be able to make statements about individual behavior it is necessary to have two force-torque sensors involved in the setup. Using only one sensor to measure the interactive forces only allows analysis of dyadic behavior which

is of limited use when one individual partner should be modeled.
3) The measurement of forces in haptic interaction comprises some challenges in relation to the definition of the cause / the *responsible partner* for a specific measured force. The interpretation of the so gained force signals is not straightforward. In line with Pan et al. [2005], measured forces can be actively applied or result from passive behavior, e.g. when *partner 1* is pulling the object not only this forces will be recorded but the second partner's force sensor will measure forces in the opposite direction as well, due to his/her arm inertia. This is true even if *partner 2* did not willingly pull in the opposite direction. Hence, it cannot be separated if the recorded individual force with the lower absolute value is actively applied or not. Figure 4.8 gives an example of individually measured forces in relation to the resulting object movement along a reference trajectory.
4) Due to the above described dynamics in this interactive task execution, one fundamental problem in haptic collaboration is that *individual* errors in action plans, i.e. forces which do not lead to a performance increase by reducing the distance between cursor and path, cannot be measured.

4.3.2 Efficiency Measures

Efficiency is generally defined by *performance* in relation to the *costs* necessary to achieve it. The concept of workload (cost or effort, which are considered equivalents here) in the evaluation of human-machine-systems was introduced by Hart and Wickens [1990]. After a short motivation, a general overview on efficiency measures is presented. Then, performance and effort measures relevant in haptic collaboration tasks are described. Finally, an efficiency measure for this purpose is provided.

In the context of haptic interaction the existing literature tends to focus on performance rather than cost (or benefits) due to the physical coupling between partners, i.e. the physical workload. However, physical effort is intuitively related to kinesthetic tasks: a) the existence of a partner may reduce the physical individual workload as the individual needs to handle only parts of the dynamics of the objects; or b) contrasting only visual coupling between partners (as possible in VR), the presence of a physical connection between partners may also be perceived as hindrance because the necessity of coordination between partners could be increased. Low coordination may thus result in additional physical costs (in terms of interactive forces as defined above). Hence, in this thesis the focus lies on physical effort contrasting mental effort as a key concept of haptic collaboration. In the following it is always referred to physical effort measures if not stated otherwise. Besides the research interest to investigate the efficiency of haptic feedback between partners for information exchange, there is further motivation to derive such a measure for haptic collaboration research:

1. The found relationship between physical costs and performance can give insights into the nature and utility of the forces or energies exchanged between partners. Based on this knowledge, more advanced forms of artificial haptic feedback for autonomous helping robots, avatars in virtual reality, and assistance functions in tele-present scenarios can be established in early stages of the design process.

2. Evaluations in the context of haptic interaction based on both dimensions (performance and effort) will give a more complete picture of possible coupling algorithms between

partners, having in mind the design of assistance functions and the model of artificial partners (compare e.g. Schaußet al. [2010]).

Next, efficiency measures from several disciplines (such as economics, (electrical) engineering, cognitive science, usability and human factors) are introduced. On this basis an appropriate measure for haptic collaboration is developed.

Efficiency measures are most widely used in economics. A common feature is the structure of measures as a ratio between an output and a resource input (e.g., purchase per staff, contracts per buyer, administrative dollars per contract [Moncka et al., 1979]. In Dumond [1994] efficiency is defined as "the amount of resources used to produce a unit of output". This efficiency measure is *relative*. That is, it allows different persons or situations to be rated against each other, but it is only meaningful within the particular comparison. The measures introduced in economics contribute to understand the general concept of efficiency, but they cannot be used to establish a specific measure in the haptic interaction context, because the performance and effort measures involved are too general.

Therefore, an efficiency measure related more closely to haptic interaction is examined: In the engineering context, the definition of efficiency conveys the benefit to describe an *absolute* measure, meaning that it can be directly interpreted without a comparison: Efficiency is "the ratio, expressed as a percentage, of the output to the input of power" (Parker [1993]) and can be formulated as

$$\text{Efficiency} = \frac{\text{Useful Power}}{\text{Total Power}} \tag{4.12}$$

Because input and output are measured on the same scale, this formula enables a percentage to be specified, which allows for intuitive interpretation of a given efficiency. Such an absolute measure would be desirable for efficiency in haptic interaction. However, this would require a measure equivalent to power, which is universal to all applications of haptic collaboration.

In Zhai and Milgram [1998] a modified version of this absolute efficiency measure is applied in a kinesthetic task, in order to quantify the efficiency of the coordination of multi-degree-of-freedom movements. Here, the authors take into account the path length that the object (or a specific edge) was moved in comparison to the path length necessary to move to accomplish the goal:

$$\text{Efficiency} = \frac{AP - NP}{NP} \tag{4.13}$$

where AP is the actual path executed by participants and NP the necessary path, which is the shortest distance between two positions. $AP - NP$ can thus be thought of as the "wasted effort" (Zhai and Milgram [1998]). Therefore, this formula describes an inverse measure of efficiency, hence called *IN*efficiency of the coordination movement. The disadvantage of this measure is that it only indirectly describes the workload by position trajectories in contrast to force measures. The author of this dissertation considers this measure to be a performance measure instead of an efficiency measure as it describes a standardized deviation from the desired path.

Another research field that provides efficiency definitions potentially relevant to haptic interaction is human-computer interaction or human-factors analysis: In addition to satisfaction, effectiveness and efficiency are the central criteria of usability in computer science. The following definitions can be found: "Measures of efficiency relate the level of effectiveness achieved to the expenditure of resources" Bevan [1995] in accordance with ISO 9241-210. Hereby, effectiveness is described by two components: a) the quantity of a task that is completed in a given time [speed] and b) the quality related to the task goals [accuracy] (ISO 9241; Frokjaer et al. [2000]). Depending on the involved resources, several efficiency measures exist. Generally, *resources may be mental or physical effort* when "human efficiency" is measured Bevan [1995]; Paas and Merri?nboer [1993]; Tullis and Albert [2008]. The authors stress the fact that these measures of efficiency are *relative*. They can be used to investigate different tasks, users [participants], or products [displays, interfaces], but are meaningful only in a specific comparison.

One specific *relative* efficiency definition in the field of human factors analysis is given in Camp et al. [2001]; Paas et al. [2005]; Paas and Merri?nboer [1993]: Efficiency is defined as a combination of performance measures and cognitive load (mental effort), where mental effort corresponds to the "total amount of controlled cognitive processing in which a subject is engaged" (Paas and Merri?nboer [1993]). In Camp et al. [2001] it is stated that "high performance with a low mental effort is most efficient and a low performance combined with high mental effort is least efficient". The authors express this conception of efficiency in terms of a two-dimensional space with a performance-axis (y-axis) and an effort-axis (x-axis), where the two measures are *z*-score standardized (mean = 0, std. deviation, = 1) to accommodate differences in measurement scales, see Figure 4.9. A reference line where Efficiency = 0 is defined by the linear function, Performance = Effort (both z-scored). This reference line is representing mean efficiency (in the given sample) under the assumption of a linear relation between effort and performance. Any particular observation of effort and performance defines a point in this space, and the corresponding efficiency can then be calculated by the perpendicular distance of the point along r to the reference line. The distance, or the absolute value of the relative efficiency measure, can be calculated as follows:

$$|\text{Efficiency}| = \frac{|\text{Effort - Performance}|}{\sqrt{2}} \tag{4.14}$$

The sign of this efficiency measure is defined in the following way: If (Effort - Performance) < 0, efficiency is positive, otherwise negative. It is mentioned by the authors that the linear relationship constitutes an oversimplification, because in many tasks performance will reach an asymptote that becomes independent of the additional invested effort.

The advantage of this measure is that due to the z-standardization, it is independent of factors that are constant across conditions of the experiment, such as the specific task that is performed. Thus, it allows comparisons of efficiency across experiments having similar manipulations, but quite different measures of performance or effort as the reference values for both dimensions are the mean of the given sample.

In Ikeura et al. [1997] an energy-based measure for cooperation efficiency is presented. However, this measure does not take performance into account, and thus, can hardly be adopted to a general efficiency measure in haptic collaboration.

Common to all the efficiency definitions noted above (except for Ikeura et al. [1997]) is that they relate two variables: one measuring the quality of behavior (output, useful power, effectiveness, performance) and the other relating to resources involved (input, costs, total power, effort, workload). Here, these words are considered synonymous [Robert and Hockey, 1997]. In general, *an efficiency measure expresses a relation between performance and effort, where efficiency is high when high performance is gained with low effort*. It is desirable to derive an

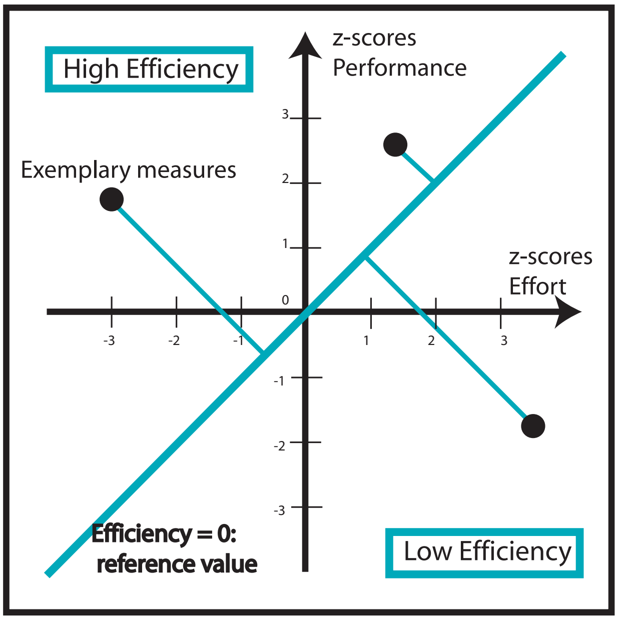


Figure 4.9: Efficiency as function of performance and effort based on the distance between a measure and the reference line the efficiency is calculated [Camp et al., 2001].

absolute measure of efficiency for haptic collaboration. This, however, requires to measure performance and effort on the same scale. Therefore, possible measures of these two dimensions are introduced in the following.

Exemplary Performance Measures in Haptic Collaboration

Task performance is described either by speed or accuracy, compare e.g. Bevan [1995]; Kerzel and Prinz [2003]. The following list of performance measures only considers objective behavioral measures, in contrast to subjective ratings.

As summarized in Appendix B, most publications in the state of the art measure position errors, time to task completion or single event errors when addressing performance in haptic collaboration tasks. Here, within these performance measures the focus is on position errors, based on the main assumption in this thesis (compare Chapter 2) that most haptic collaboration scenarios can be abstractly represented by shared trajectory following. Thus, any kind of displacement measure between the desired and actual trajectories is of interest and represents the accuracy aspect of performance. The so-derived measurement will allow us to analyze the experiments presented in Section 4.2. However, there is a clear drawback in performance measures based on differences between desired and actual trajectories: the shared trajectory needs to be known to use displacement performance measures. This is mainly the case in experimental setups, but not necessarily in real life applications where the environment can be less structured. Thus, this measures can serve only to find generic rules but can not be part of controllers for robotic partners. Some exemplary performance measures are summarized here:

A) Root-mean-square error (RMS) is based on the displacement between the desired and the actual position of a given object over several time steps or repetitions. Here, an example is given for the one-dimensional case:

$$RMS = \sqrt{\frac{\sum_{k=1}^{N}(x_{o,k}^d - x_{o,k})^2}{N}} \tag{4.15}$$

where $x_{o,i}^d$ is the desired position, $x_{o,i}$ the actual position and N the number of samples in the examined interaction sequence. The advantage of the RMS in contrast to the mean absolute error is that the RMS punishes large displacements stronger. Hence, it is assumed that the signal to noise ratio in this measure is increased. RMS and other displacement measures give precise information on accuracy but do not take into account the speed of a task.

B) Time on target (TOT) is the percentage of desired behavior throughout one trial. By distinguishing only between correct and erroneous behavior for each time step, an absolute measure can be derived. Thus, it represents the time when the task was performed “correctly”.

$$TOT = 100\frac{\sum_{k=1}^{N} OT_k}{N} \tag{4.16}$$

$$OT_k = \begin{cases} 1 & \text{if } x_{o,k}^d - x_{o,k} \leq TOL \\ 0 & \text{otherwise} \end{cases} \tag{4.17}$$

where $x_{o,i}^d$ is the desired position, $x_{o,i}$ the actual position, N the number of samples in the task length examined and TOL a possible tolerance value for the accuracy.

Because of its binary nature (on/off target), this measure is generally less precise than the RMS but offers other advantages: Using Bevan [1995]’s definition of temporal efficiency, TOT is already an efficiency measure, as it relates a qualitative behavior aspect (correct/incorrect) to a resource, here time. However, the goal in this section is to introduce physical effort as costs, and hence TOT can be utilized as performance, but not as efficiency measure.

C) Time to Task Completion (TTC) is another well-known performance measure. It relies on speed aspects exclusively and is not addressing accuracy.

D) Single-event errors: Examples for this measure in the context of haptic tasks are e.g. dropping a box (e.g. Sallnäs [2001]) or bumping into the wall of a labyrinth (e.g. Glynn et al. [2001]). The measure is highly task specific and thus, no list is given here.

Performance measures are highly task-related (for an overview on further measures see e.g. Jagacinski and Flach [2003]). Hence, depending on a given task, more specialized performance measures might be suitable. Furthermore, it is important to be aware of the correct interpretation of the performance measures: While high TOT measures describe good performance, it is the other way around for RMS and TTC, because here smaller values are desirable. Hence, the two latter measures lead to inverse performance statements and in relation to the effort measure would lead to *IN*efficiency measures rather than to efficiency scales. To summarize it can be stated that there is a variety in possibilities to measure performance in haptic collaboration. By choosing a task to conduct an experimental study in this context, the performance measure is indirectly derived depending on the task goals.

Effort Measures in Haptic Collaboration

In jointly executed kinesthetic tasks a physical effort measure has to be related to forces. Only in this way can we address the effort (= the costs arising for the individual accomplishing the

	Individual level (i)	Dyadic level (d)
Movement effort	$\mathrm{MAF}^E_{1,i} = \mathrm{fcn}(f^E_1(t))$	$\mathrm{MAF}^E_d = \mathrm{MAF}^E_{1,i} + \mathrm{MAF}^E_{2,i}$
Interaction effort	$\mathrm{MAF}^I_{1,i} = \mathrm{fcn}(f^I_1(t))$	$\mathrm{MAF}^I_d = \mathrm{MAF}^I_{1,i} + \mathrm{MAF}^I_{2,i}$
Total effort	$\mathrm{MAF}^T_{1,i} = \mathrm{MAF}^E_{1,i} + \mathrm{MAF}^I_{1,i}$	$\mathrm{MAF}^T_d = \mathrm{MAF}^E_d + \mathrm{MAF}^I_d$

Table 4.1: Effort measures based on interactive and external forces separated for individual and dyadic level; the individual level is shown as indexed for partner 1.

task, here the physical effort) which arises from coordination with the partner in addition to the forces necessary to manipulate an object. Furthermore, effort can be measured by the movement executed during object manipulation. The combination of this movement effort with forces leads to power- or energy-based measures, which consider force *and* motion.

A) Force-based Effort Measures: Based on the forces components introduced in Section 4.3.1, an effort measure for a given haptic collaboration task is now derived MAF (= mean absolute forces, see Equation (4.18)). To derive this measure in a meaningful way, movement and interaction effort are distinguished. *Movement effort* is based on individual external forces and directly influences the position of the object. Therefore, it is also related to the accuracy part of performance, the qualitative outcome of such movements. *Interaction effort*, however, could influence the communication between partners, helping to establish mental models of the partner or determining roles. Thus, interaction effort could lead to high performance indirectly. Hence, the total effort MAF^T is the sum of the movement effort based on external forces MAF^E and the interaction effort MAF^I in a given interaction sequence. Because the sign of the forces is defined by direction, which does not influence effort, the absolute force is considered (MAF = mean absolute force).

$$\mathrm{MAF} = \frac{1}{N}\sum_{k=1}^{N}|f(k)| \tag{4.18}$$

with N the length of the task, one trial or data set and f the respective force component.

$$\mathrm{MAF}^T = \mathrm{MAF}^E + \mathrm{MAF}^I \tag{4.19}$$

where MAF is the mean absolute force.

In general, effort can be described on an individual (MAF_i) or dyadic level (MAF_d, which is indicated by the subscript i and d, respectively). Based on this analysis, effort measures are defined as a function of the respective forces and listed in Table 4.1.

One important control condition in haptic collaboration research is a condition where no haptic feedback between partners and possibly the object is provided. Thus, the effort measure should be applicable to this condition as well, to allow a comparison of efficiency values resulting from those control conditions. However, f^I is not relevant in vision feedback condition, as it is not felt and has no meaning. Instead, the partners are coupled by some algorithm determining the object position without feeling each others forces (in the experiments presented here the object position resembles the mean of the two individual inputs). Under this condition, f^I measures only the forces required to move the inertia of the object. Thus, they represent the error due to the static definition. Therefore, the force-based effort measures are not directly comparable between a mutual haptic feedback and a vision condition. In addition, it is assumed that in this condition the physical effort arising for a partner is rather motion than force determined: The individual can only infer what the partner is doing by comparing his/her own input with the resulting cursor position (compare Groten et al. [2007, 2009c]). In the case of misinterpretations, additional movements are required to produce the desired object movements. A power-based effort measure, which considers the movement effort, is presented next to overcome those drawbacks.

B) Power-based Effort Measures: While overcoming some of the disadvantages of the force-based effort measure, a power-based effort measure also offers the following benefits: effort measures in engineering are mainly based on power $P = vf$ or energy $E = \int P$. Consequently, energy-based approaches are widely used in robotics in the context of haptic interaction, especially in teleoperation (Anderson and Spong [1988]; Hokayem and Spong [2006]; Niemeyer and Slotine [1991]). Power as a mean of measuring effort is considered in relation to the definition given in Section 4.3.1.

It is intuitively clear that a higher energy flow relates to a higher physical effort. But, not only a positive energy flow, i.e. energy injection to the system (e.g. acceleration of the virtual object), causes physical effort for the operator, but also a negative energy flow, i.e. dissipating energy from it (e.g. deceleration of the virtual object). For this reason, this effort measure is defined as the mean absolute power (MAP) in a given interaction sequence:

$$MAP_d = MAP_{1,i} + MAP_{2,i} = \frac{1}{N}\sum_{k=1}^{N} |\boldsymbol{P}_{1,k}| + \frac{1}{N}\sum_{k=1}^{N} |\boldsymbol{P}_{2,k}| \tag{4.20}$$

where $\boldsymbol{P}_{1,k}$ and $\boldsymbol{P}_{2,k}$ is the energy flow at the respective interfaces/interaction points at a given time step k ($k = 1 \ldots N$). Again, the indices i and d indicate if the measure is on the individual or dyadic level.

Despite the above mentioned advantages of this measure, it also has some drawbacks: Only total physical effort can be considered with power based effort measures, and no distinction between movement and interaction effort is possible. Furthermore, in the case that both partners push against each other without moving the object, the effort is measured as zero, which does depict the workload in accordance with the physical definition. However, it may still require isometric contraction of the partner's muscles, leading to perceived workload. Despite this definition problem, this measure allows us to compare effort values from conditions with and without haptic feedback between partners, as a common comparison in haptic collaboration research.

Note, that in line with the static definition of force components proposed in Section 4.3.1, the effort measures introduced here are not able to measure effort due to object dynamics or effort related to a partner, which has to be move a passive partner's arm in addition to the object. Furthermore, it is important to note that we took the mean of the effort measures to derive one value representing an interaction sequence/trial. Then, a comparison between interaction sequences is only given when the trial length is constant. With varying trial length it is advisable to integrate over time instead.

Efficiency Measures in Haptic Collaboration

To approach the targeted absolute measure of efficiency for haptic collaboration, it is necessary to express effort and performance on the same measurement scale. Describing the effort by the deviation from the desired and actual path as in Zhai and Milgram [1998] does not seem appropriate here, as the forces exchanged between partners are of high interest and should be addressed in the effort measure. Thus, the solution to this absolute measure problem could lie in a force based performance measure. However, that would require knowing the desired force, which is the necessary effort, in a given task. This is possible in individual task execution as it can be derived from a known, desired object trajectory. Though, when working with a partner, the desired force to achieve maximum task performance applied by partner 1 is highly depending on the force applied by partner 2 as stated before. This force applied by the partner cannot be predicted. Furthermore, at this point there is no information on how much effort is necessary for the interaction itself. Due to the interaction between partners in haptic collaboration, such a force-based performance measure could only be derived on a dyadic measurement level. As a general goal in this line of research is to gain an individual model and to understand the interaction between partners to develop shared action plans out of individual action plans, this solution is refused here, even though, in specific tasks and with more pre-knowledge on the interactive behavior such an absolute measure may be developed in future. Hence, a relative measure is introduced in the following.

A modified version of the measure introduced in the field of human factors is adopted because it is more precise than definitions found in the economic or usability context and allows considering physical effort. The efficiency measure is based on the distance efficiency measure [Camp et al., 2001; Paas et al., 2005; Paas and Merri?nboer, 1993], depicted 4.9. It allows for comparing efficiency, for example,

- between dyads in a given sample
- between two partners of a dyad
- between conditions such as different partners, displays, tasks and feedback conditions

For the following experiments on haptic collaboration the efficiency measure is defined to be:

$$\Lambda(B,\Gamma) = \frac{Z(B) - Z(\Gamma)}{\sqrt{2}} \tag{4.21}$$

where $Z(B)$ is a z-standardized performance measure and $Z(\Gamma)$ a z-standardized effort measure. In contrast to the procedure presented by Camp et al. [2001]; Paas et al. [2005]; Paas and Merri?nboer [1993], the absolute values are not calculated first and the sign corrected afterwards, but this is done directly in the formula. Being scale-independent due to the z-standardization the performance and effort measures now represent deviations from the mean values found in the overall data set. Whether this measure expresses the dyadic Λ_d or individual $\Lambda_{1,i}$, efficiency depends on the level of the performance and effort measures involved. Furthermore, it is distinguished between interactive Λ^I, external Λ^E, and total Λ^T efficiency; again depending on the implied effort measure. This efficiency measure is discussed in more detail in relation to the specifically used performance and effort measures in the context of the efficiency analysis in Chapter 5.

4.3.3 Dominance Measures

Addressing the second research interest outlined in Subchapter 4.1, this section develops dominance measures for haptic collaboration research. The dominance concept plays an important role in action plan negotiation on both levels of haptic collaboration. In line with the framework presented in Chapter 2, on the lower level it needs to be negotiated how the two individual force inputs are chosen to follow a shared trajectory. Due to the relation to the applied forces, this dominance on this level is called *physical dominance*. On the higher level, the shared trajectory itself needs to be negotiated, if several possible trajectories exist. The decision on this trajectory is related to higher level *cognitive dominance*. In the following, these two dominance measures are outlined in detail. The first part deals with dominance in low-level, the second with dominance in high-level haptic collaboration.

Dominance Measure for Low-Level Haptic Collaboration

Before an overview on dominance measures in literature is given, a definition of dominance in low-level haptic collaboration is derived: the partner who applies higher forces (in one dimension) on the object is controlling the object movement to a higher degree (in this dimension) and can thus be considered dominant (in this dimension) on the low-level of haptic collaboration. This partner determines the shared action plan on how to follow the desired trajectory to a larger extend than the partner. This dominance type is also referred to as physical dominance.

Dominance *parameters* (mainly termed α) are used in state-of-the-art control architectures for human robot interaction and technically mediated interactions between two humans, e.g. Evrard and Kheddar [2009]; Khademian and Hashtrudi-Zaad [2007a,b, 2009a,b]; Nudehi et al. [2005]. However, to the author's best knowledge, only two approaches exist which deal with the *measurement* of dominance:

A measure of dominance for experimental human-human interaction data is developed in Reed et al. [2005]. There, dominance of one dyad member is defined on the basis of individually applied forces:

$$C_1 = \frac{f_1}{f_{sum}} \tag{4.22}$$

C_2 is calculated correspondingly. The authors assume that these two measures range from 0 to 1, and the two measures add up to 1. However, it is important to note that this measure of dominance can only be considered standardized when individual forces of both partners are applied in the same direction, meaning that no interactive forces occur. *Only then* is $C_1 \in [0, 1]$ and thus $C_1 + C_2 = 1$. Using these measures also in situations when interactive forces are applied, comparability of dominance across different dyads or experimental conditions is not ensured. The authors changed this measure in Reed and Peshkin [2008] and divided $\int f_1$ by $\int f_{sum}$. The integral was calculated over phases of contemporaneous acceleration or deceleration of both partners, neglecting phases with interactive forces. This also implies that calculation per time-step is no longer possible, limiting the usage in modeling technical partners.

It has to be mentioned that in Corteville et al. [2007] an assistance function for one DoF point-to-point movements is designed which allows a scaling of the assistance level. This scaling (denoted as α) allows to vary the control of the assistance function over joint movements between 0 and 100%. In contrast to all other two approaches , this α -value is velocity and not force related.

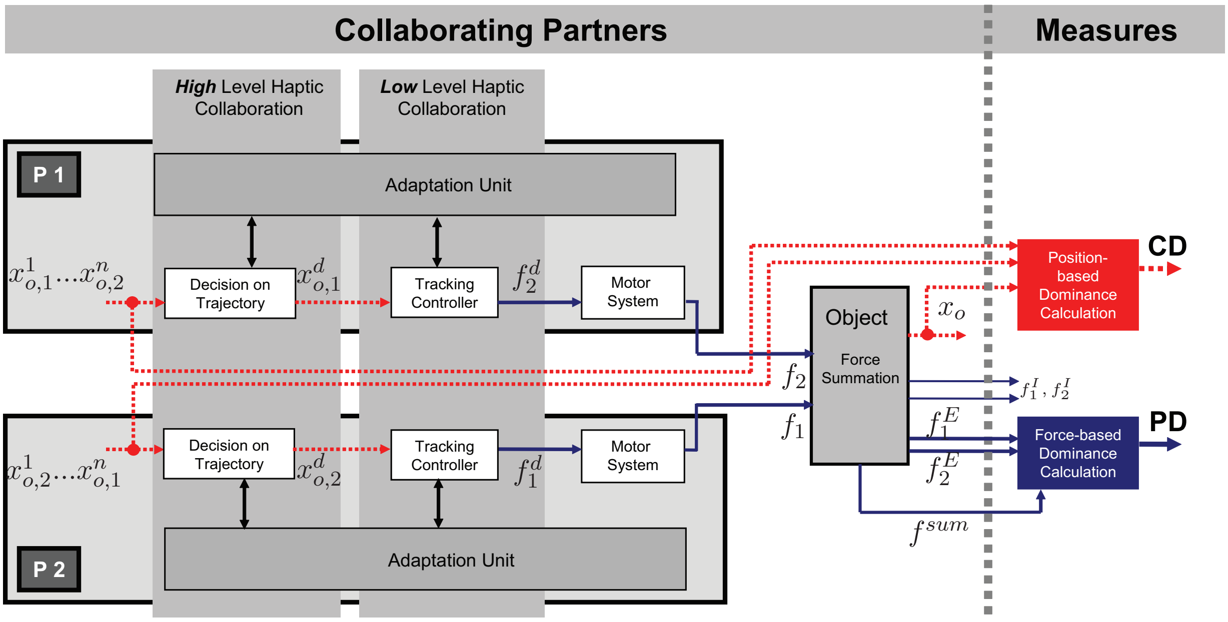


Figure 4.10: Relation between the framework introduced in Chapter 2 and the dominance measures. Note, that dominance is introduced as *measures* and not as parameters of the human model. *CD* refers to cognitive dominance and *PD* to physical dominance. *Physical* dominance is based on the ratio of individually applied forces which accelerate the object, i.e. f^E and the forces summed from both partners, which operate on the object (f^{sum}). The force decomposition into interactive (f^I) and external forces (f^E) is calculated by the force summation in the jointly manipulated object. *Cognitive* dominance is position-based and is calculated as the difference between the individually planned object trajectory ($x^d_{o,2}$ or $x^d_{o,1}$) and the actual object trajectory resulting from haptic collaboration. It is position-based and relates to the deviation between the actual object trajectory and the desired individual trajectories.

Therefore, speed-profiles of a given task have to be implemented in advance, which reduces the generalizability of this approach. Furthermore, in case that the estimated speed-profile does not match the actually executed one, the domiannce measured in the actual interaction between assistance and human may vary from the a priori set α-value. Thus, the comparison to force-based dominance measures is limited.

Now a dominance measure for haptic collaboration, which can serve as a basis for controller design and evaluation of haptic human-robot collaboration is developed. Based on the force components introduced in the previous section, a force-based physical dominance measure is extending the above summarized state of the art. This dominance measure is derived for one dimension only. But, it can be generalized to multidimensional object motions by e.g. taking the mean dominance of all dimensions. It may, however, be advantageous to know dimensions specific which partner is dominant. The dominance measure is founded on the measure proposed by Rahman et al. [2002a]: A dominance factor α is introduced as “distribution ratio” or “factor of inertia”. The individual values can range from 0 to 1 and are complementary (i.e. $\alpha_1 + \alpha_2 = 1$). This complementarity of dominance variables is consistent with definitions from social psychology (compare Chapter 6). The research group (Rahman et al. [2002a]) experimentally investigated the dominance between two human partners in a 1 DoF pointing task. As they claimed measuring interactive forces between two human partners is impossible (being right for the dynamic case, not the static one), they used a correlation analysis between the acceleration of the jointly manipulated object and the individually applied forces to address the dominance distribution. The disadvantage of this procedure, beside limited explanatory power (correlations do not reflect the amplitude of forces) is that the correlation can only be calculated offline. The distribution ratio is defined as follows:

$$f_1 = \alpha m\ddot{x} + f_{int} \tag{4.23}$$

$$f_2 = (1-\alpha)m\ddot{x} - f_{int} \tag{4.24}$$

where f_{int} are defined as internal forces by the authors, equivalent to the here defined interactive forces f^I. After illustrating that a mathematical calculation of α is impossible, the authors state that "it is also difficult to determine the value of α analytically because the nature of internal forces is unknown". This seems to be correct for a dynamic measurement of the internal forces, which is not available. However, the internal forces can be measured in a static way, as shown in Section 4.3.1, where different force components are defined. As stated there, the static measure is assumed to be appropriate when the object has a small mass and is moved in free space (no damping). The static measure can still give valuable insights into haptic collaboration. Thus, the low-level dominance measure can be defined in accordance with Rahman et al. [2002a].

Equation (4.23) is also related to Reed et al. [2005]. However, it considers the individual external forces instead of the overall forces applied by the individual. This has to reasons: a) the dominance measure should describe which partner has higher control of the object movement. As only external forces are responsible for object acceleration it seems intuitive to employ them when developing a dominance measure; b) The measure defined by Reed et al. [2005] can measure dominance only if both partners apply forces in the same direction. This problem is overcome by using the external forces. The interactive forces are important for describing the individual effort a partner applies, but they do not contribute to the dominance measure.

Consequently, the individual dominance of partner 1 over 2 (PD_{12}) can be defined as

$$PD_{12,t} = \frac{f^E_{1,t}}{f_{sum,t}} \tag{4.25}$$

where t is the corresponding time step. The same also holds for $PD_{21,i}$. The attributes common to most dominance measures in literature are existent as well: $PD_{12} \in [0,1]$ and $PD_{12} + PD_{21} = 1$. Thus, a partner is absolutely dominant with a value of one, and absolutely non-dominant with a value of zero. If there are interactive forces in the time step, the partner who applies only interactive forces (the smaller amount of forces, compare Equation (4.9)) is per definition non-dominant. A value of 0.5 means, that both partners equally share the workload required to accelerate the object. The individual dominance measure is independent of the direction of the individual forces f_1 and f_2. It can be calculated for each time step, contrasting Reed and Peshkin [2008]. To describe the dominance distribution between partners for the whole task or interaction sequence, the absolute mean dominance behavior ($\bar{PD}_{12}$) can be calculated.

For some analyses in haptic collaboration, a measure which describes the dominance behavior on a *dyadic level* can be necessary. Hence, a measure describing the amount of the dominance difference, meaning the amount to which one partner dominates the other is derived additionally:

$$\bar{PD}_{diff} = \left|\bar{PD}_{12} - \bar{PD}_{21}\right| \tag{4.26}$$

This measure circumvents the problem of interchangeability of the interacting partners. The value is independent of the constellation, i.e. if partner 1 dominates partner 2 or vice versa.

Figure 4.10 depicts the relation between the measure of physical dominance and the conceptual framework presented in Chapter 2. It is illustrated how the applied forces influence the physical dominance measure (PD). It can be seen that the physical dominance relates to forces only. Next, the position-based cognitive dominance (CD) measure is introduced.

Dominance Measure for High-Level Haptic Collaboration

A measure on high-level haptic collaboration has to address which partner is dominating the *decision on the shared trajectory* of the jointly manipulated object if there exist different possibilities for this trajectory. In contrast to the physical dominance defined above, this dominance measure is, thus, not force- but position-based. It is named *cognitive dominance* and the measure is related to physical dominance and the framework described in Chapter 2 in Figure 4.10.

It is evident that those two measures are not independent of each other: To convince one partner via the haptic communication channel to lift an object higher (choosing this trajectory) while the overall goal is to execute a horizontal movement for example implies that forces are applied in this direction. Thus the cognitive dominant partner needs to be physically dominant at some point. However, it is questionable that it is always true that the partner who carries more weight, thus is more dominant on the lower level, also decides on the object trajectories. This question will be addressed in Chapter 6. For now it is assumed that in a given interaction sequence the cognitive dominance (CD) in decision situations is related to physical dominance in this situation (PD_{12}) by some function f which is unequal to zero:

$$CD_{12} = \text{fcn}(PD_{12}), \text{with fcn} \neq 1 \tag{4.27}$$

For cognitive dominance to take place, it is necessary that different object trajectories exist. Furthermore, it is a prerequisite to know the individual action plans about the trajectory, i.e. the individually desired trajectories. Then, a cognitive dominance measure should quantify to which amount the shared action plan, and thus, the resulting object movement is following each of the individually planned trajectories. This is fulfilled by

$$CD_{12} = \begin{cases} 0.5 & \text{if } x_1^d = x_2^d \\ min(1, max(0, \frac{x_o - x_2^d}{x_1^d - x_2^d})) & else. \end{cases} \tag{4.28}$$

where CD_{12} is the cognitive dominance of partner 1 over 2 in a given decision situation (DS), x_o is the actual position of the virtual object and x_1^d and x_2^d the individually desired trajectories of the two partners. Due to the fact that the actual object trajectory does not necessarily lie between the two desired trajectories (e.g. when there is an overshoot due to falsely assumed object dynamics) the above given saturations have to be made. Cognitive dominance, thus, takes the Euclidean distance between the individually planned and actually jointly executed trajectory into account to determine, which partner is influencing the decision on the object trajectory to a higher amount. The measured values lie between 0 and 1 and are complementary for the partners. A values of 0 implies non-dominance which his given when there was a difference between individual desired trajectories and that the dyad then executed the trajectory planned by the other partner. A values of 0.5 in cognitive dominance can have two origins: a) the executed trajectory lies exactly between the two individually desired trajectories; b) the two desired trajectories are identical as it represents $x_1^d = x_2^d$. Both situations are considered equal in terms of dominance as no partner overrules the other. A value of 1 implies high dominance.

The actual object trajectory is observable; no challenges for measurement exist here. However, gaining knowledge on the individually desired trajectories can be difficult as they are latent cognitive concepts (not observable). The desired trajectories can be addressed by questioning the participant or user during task execution. Another way is to control these individual desired trajectories experimentally by explicit instructions as it is given in the here presented experiments (compare Section 4.2.4). In the author's opinion that is the best way to investigate the individual action plans, however, the procedure is based on the assumption, that participants actually plan to follow the path exactly.

Generally, the data on latent concepts can be of lower reliability than direct measures as they are inferred indirectly. Therefore, a simplified measurement of cognitive dominance for exploratory use of this concept is proposed: CD^b. It can be applied if the following conditions hold:

- a finite number for possible object trajectories (as in the example of obstacle avoidance)
- an individual preference on one of these options is instructed, and thus, its execution measurable

which is true for the experiments introduced in Section 4.2. It is required to code the dominance in a decision situations where the individually desired trajectory is equivalent with the executed as one and coding the opposite case as zero. If both partners agree on an action plan, i.e. there is no negotiation the joint trajectory in a given decision situation, cognitive dominance can be coded as 0.5. When several decision situations ($\sum DS$) are part of the given interaction sequence, the value for mean cognitive dominance is defined as the sum of these coded values standardized by the total amount of decisions taken. The mean cognitive dominance for partner 1 is then:

$$\bar{CD}^b_{12} = \frac{\sum_{i=1}^{k} CD^b_{12,i}}{k} \tag{4.29}$$

where $\sum_{i=1}^{k} CD^b_{12,i}$ are the values of cognitive dominance of partner 1 over partner 2 in a sequence of k decision situation ($k = \sum DS$) based on the above-described coding schema. The same also holds for $\bar{CD}^b_{21}$.

4.4 Conclusion

This chapter introduced tools for the experimental investigation of human behavior in haptic collaboration. Two new experimental designs and the corresponding setups have been explained to enable an investigation of the two central research questions raised in this thesis: A) if intention negotiation via mutual haptic feedback is possible (addressed by an efficiency measure) and B) how two individual contributions to a shared action are combined (addressed by a dominance measure). The two experiments are investigated in the two levels of haptic collaboration, i.e. how and where to move an object, iteratively. Thus, they can serve as a tool to validate the haptic collaboration framework presented in this dissertation. The experiments introduced here are a profound method to study far more research questions than the two mentioned. Shared decision making and intention negotiation can now be studied on an experimentally controlled manner. The form in which the individually desired trajectory is transformed from a latent concept to a measurable one, enables a quantitative investigation of deviations from the individually desired trajectories due to the collaboration with a partner. Thus, a general contribution to future investigations on haptic collaboration could be made.

In addition, measurements in the context of haptic collaboration have been introduced. For the first time, force and energy components of relevance in this line of research have been discussed in detail. Again, this serves as a general basis to conduct future analyses of haptic collaboration experiments. Two explicit measures were introduced then: The presented efficiency measure allows for the first time in haptic collaboration research to relate task performance to required physical effort. This is a valuable measure to evaluate robotic partners and assistance functions in haptic tasks as can e.g. be seen in Schaußet al. [2010]. The measure is also suitable for individual task execution. The efficiency measure can easily be adapted to different tasks and various performance and effort measures, and thus, is of general interest. The second measure introduced is a dominance measure. This measure is subdivided into two types in line with the levels of haptic collaboration introduced in the framework. The physical dominance measure enables statements on the individual force contribution to the acceleration of a jointly manipulated object. Cognitive dominance measures on the other hand can derive knowledge on the accordance between individually planned trajectories and jointly executed trajectories of an object in shared decision situations as e.g. part of obstacle avoidance. The two dominance measures are of high relevance to gain insights into human behavior as parameters corresponding to physical dominance in robotic architectures are already state of the art. However, only little knowledge exists on appropriate physical dominance behavior in haptic collaboration with humans. Cognitive dominance has not been addressed in literature so far. As a first attempt to measure latent concepts in haptic collaboration, here the desired trajectory, this measure can clearly enhance research towards human-like behaving robotic partners in haptic collaboration.

Based on the experimental designs and measures presented here, the next two chapters report analyses of these experiments addressing the two research questions.

5 Intention Negotiation: an Efficiency Analysis

The possibility to integrate the individual intentions is a prerequisite for collaboration between two partners. Then, intention negotiation is required in case the individual intentions differ. Despite this interest in intention negotiation, in haptic collaboration no experiments have been conducted yet, which show that "haptic communication" exists[1]. If, however, intentions cannot be negotiated via this channel, it is doubtful that the implementation of corresponding behavior on robotic partners is necessary. Taking into account the challenges of implementing mutual haptic feedback, it is of high interest to know the scenarios, which benefit from this potential communication channel. The design of haptic interaction control architectures is challenging enough [Arai et al., 2000; Buss et al., 2007; Kazerooni, 1990; Wang et al., 2004], even if the transfered signals are not considering intentions communicated with human users.

After the presentation of a conceptual framework of haptic collaboration (Chapter 2) and the introduction of experimental designs and measures, which enable systematic research within the framework (Chapter 4), this chapter describes the analyses of two experiments. These experiments answer the question of whether intention negotiation via mutual haptic feedback[2] is possible between human partners.

Mutual haptic feedback, which is optional in virtual scenarios, could positively influence the joint task performance. However, it could also generate disturbance for the individual partner, who eventually has to overcome the partner's forces relating to different individual action plans. Therefore, it is argued that an analysis should not only investigate the performance (dis-)advantages of human-like mutual haptic feedback for intention negotiation, but also the physical effort related to it. Hence, in this chapter, efficiency analyses are executed, which address the performance in relation to physical effort. This measure helps to draw conclusions on the existence of intention negotiation. Results will show stable performance in situations, which require increased intention negotiation indicating that intention negotiation takes place. The effort measure provides evidence that the haptic communication channel is actually utilized. Haptic collaboration between two human partners is studied as a reference for human-like behavior within a jointly executed tracking task. In order to understand the role of mutual haptic feedback for intention negotiation between humans in kinesthetic tasks, a control condition where such feedback is not provided is required. Therefore, in the two experiments reported separately in the next subchapters, a control condition is employed where haptic feedback is given from the manipulated object only. Furthermore, in these two experiments, intention negotiation on the basis of mutual haptic feedback is investigated iteratively in line with the two levels of haptic collaboration, see Figure 5.1. These levels relate to the two types of intentions, which have to be

[1]apart from the related publications by the author of this dissertation [Groten et al., 2009b, 2010]

[2]Mutual refers to the fact that both partners are able to perceive and act upon each other via this signal exchange allowing adaptation processes, which is a prerequisite for collaboration. Thus, it is associated with human behavior here, compare also Section 1.3.

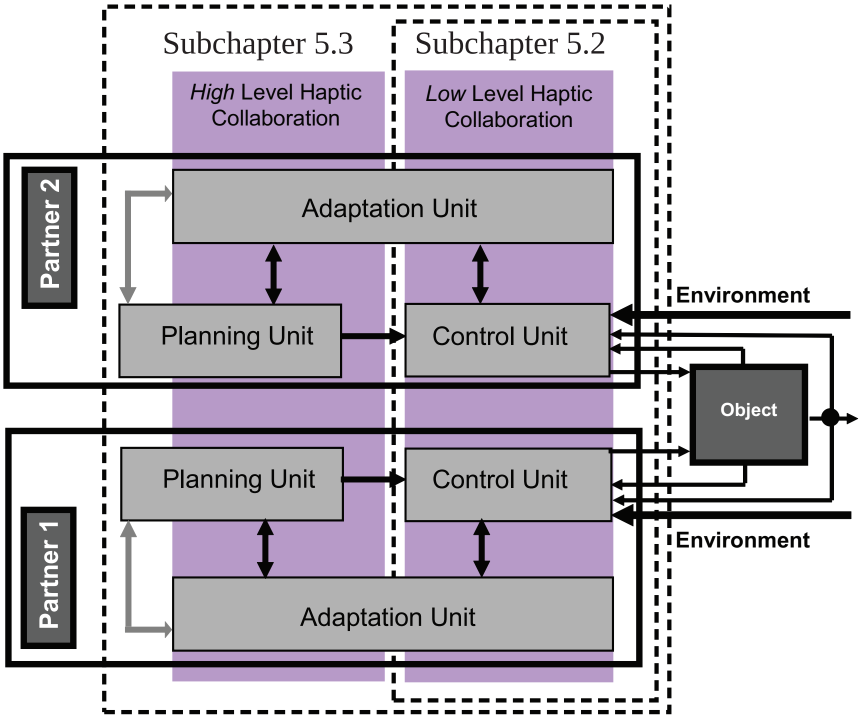


Figure 5.1: Structuring this chapter within the haptic collaboration framework as described in Chapter 2: The efficiency analysis presented in the following addresses intention negotiation on how (lower level) and where (higher level) to move a jointly manipulated object.

negotiated: On the lower level it has to be decided *how* to move an object. Strategies to combine the individual force inputs have to be found. On the higher level it has to be decided *where* to move the object, i.e. shared decisions on the object trajectory have to take place.

First, a literature overview on effects of haptic feedback on performance and effort is presented. The following two subchapters experimentally address efficiency on the two different levels of haptic collaboration to gain insights on the benefit of mutual haptic feedback for intention negotiation. This chapter ends with a general conclusion including guidelines for the development of robotic partners inferred from the results on human-human collaboration presented in this chapter.

5.1 Literature Overview

Human-robot haptic collaboration is not yet a well studied subject (see Hoffman and Breazeal [2004] and compare Section 3). However, studies exist which are of relevance in the context of efficiency, i.e. the relation between effort and performance, and intention negotiation in joint tasks. These are discussed in the following.

Several authors suggest that providing haptic feedback from the virtual environment, where *task execution takes place by one individual*, leads to higher performance (Biocca [1992]; Burdea and Coiffet [1994]; Gupta et al. [1997]). Also, in the context of supervisory control and tele-operation a positive effect of haptic feedback on individual task performance could be shown (Das et al. [1992]; Hannaford et al. [1991]; Howe [1992]; Lee and Kim [2008];

Massimino and Sheridan [1994]; Sheridan [1992]). Furthermore, in training contexts, i.e. learning of motor skills it was found that haptic guidance leads to an increase of performance in individual task execution (Avizzano et al. [2002]; Feygin et al. [2002]; Morris et al. [2007]; Oguz et al. [2010]; Ström et al. [2006]).

To investigate the question whether the advantage of haptic feedback in performance can be found in *joint task execution* (two collaborating humans) as well, several experimental studies have been conducted: In Basdogan et al. [2000] a non-haptic condition is contrasted with a haptic condition that provided feedback from the environment, including the interaction partner, in a “ring-on-wire game”. The task completion time as well as the time per successful trial were higher when haptic feedback was provided. The same conditions (with either none or full haptic feedback) were compared by Sallnäs et al. [2000]; Sallnäs [2001]; Sallnäs and Zhai [2003]. Participants were asked to jointly manipulate cubes in a virtual scenario. Performance did not differ in terms of task completion time, but the number of cubes falling down because of insufficient interaction was decreased with haptic feedback. In a two DoF self-paced tracking task for two persons with different control-architectures of input devices Glynn et al. [2001] compared force feedback conditions to those without such feedback. Not providing force feedback led to better performance than a condition with force feedback, where partners were coupled with a virtual spring. However, the results are challenging to interpret as the experimental plan with the two control-architectures and feedback conditions was not fully crossed. In all these experiments, the haptic feedback was either given from the partner *and* the environment, i.e. the manipulated object or no haptic feedback at all was provided. Hence, the found advances in performance can possibly be explained by the effect of haptic feedback provided by the object, which has been shown in individual task execution research. Thus, whether mutual haptic feedback between the two partners, i.e. the haptic communication channel leads to increased performance can not be answered explicitly by those studies. One study, which suggests that a general effect of haptic feedback instead of a collaboration specific effect, is presented by Ullah et al. [2010]. There, in a virtual reality experiment, artificial forms of haptic feedback provided by coordination controllers between partners did not increase performance compared to simple force feedback from the object.

In the studies described in the following, individual and dyadic task performance have been compared when executing the same task with haptic feedback. Hence, the feedback condition is constant, and the effect of a partner can be studied instead of a general haptic feedback effect: Interaction with haptic feedback was contrasted with single-person task execution by Reed et al. [2004, 2006]; Reed and Peshkin [2008]. The authors analyzed real human-human interaction in a one DoF pointing task. Results showed that dyads performed better than individuals with respect to task completion time. The *individual* forces were higher when acting alone compared to acting within a dyad. This may be caused by the partner as a hindrance to smooth task execution. The authors report that few dyads had a feeling of cooperation, most perceived the partner as interference [Reed and Peshkin, 2008]. To overcome the challenge that performance advances in dyadic task execution could be explained by the additional physical resources of a partner the rotational inertia has been adjusted (doubled for dyads) to provide equal workload for the individual whether interacting with a partner or not. Similar experiments with one DoF rotational pointing tasks have been executed by Gentry et al. [2005] and Ueha et al. [2009]. Both studies report increased performance for dyads compared to individuals. In Feth et al. [2009b]

performance and energy of dyads in contrast to two individual conditions has been studied, using the experimental tracking task setup reported in this thesis. Performance was higher for dyads, and an energy exchange between partners was found. In one of the "alone" conditions the object dynamics where adjusted to achieve comparable workload conditions for the individuals in the "alone" and the collaborative task execution. The other "alone" condition was not adjusted to serve as a control condition. Taking this into account, the here mentioned studies suggest a positive effect of haptic interaction on performance, as the advantage of a reduced workload is experimentally adjusted. However, it remains unclear if the advantages of mutual haptic feedback are due to an efficient intention recognition between partners, or if there are alternative explanations as a stabilization of the movement due to interactive forces. The idea that "contradictory forces" lead to an advanced control of perturbations is experimentally addressed in Reed and Peshkin [2008], but was not supported by results.

There is one study which compares a) a collaborative haptic feedback condition to b) an individual task execution and c) dyadic performance with haptic feedback from the manipulated object but not from the interacting partner [Feth et al., 2009c]. The task conditions did not influence the error in a two dimensional pointing task, executed telepresent with four dimensional interfaces. However, task completion time was significantly decreased in the collaborative haptic feedback condition, whereas there was no significant difference between the other two conditions. Again, this implies evidence for a benefit in performance based on the communication channel provided by the haptic feedback.

The only studies in the above mentioned kinesthetic interaction experiments which recorded effort measures such as force and energy next to performance are the ones by Reed et al. [2004, 2006]; Reed and Peshkin [2008] and Feth et al. [2009b,c]. However, the effort measures are not related to the performance in these tasks. Thus, to the best of the author's knowledge, no experimental study has been conducted to date addressing efficiency in haptic human-human collaboration (except for the publications based on this chapter: Groten et al. [2009b, 2010]).

Efficiency has not been investigated in joint kinesthetic tasks with mutual haptic feedback between partners. However, theoretical, task-independent knowledge of the relation between effort and performance can provide information on basic mechanisms: It is generally assumed, that humans prefer to achieve their action goals with a minimum of effort, whether this is mental or physical effort. For example, Robert and Hockey introduced a cognitive-energetical framework (Robert and Hockey [1997]) with a compensatory control mechanism within a human operator to address the trade off between performance and costs (effort) based on Kahneman [1973]. The idea is, that performance is "protected" by allocation of further resources. The alternative to this behavior is seen in a stable amount of involved resources leading to a possible lower performance with increased task requirements. In this model those resources are related to subjective mental effort. However, in the given context a generalization of this thought towards physical effort is proposed as research topic.

Based on findings that group performance is influenced by the ability of group members to exchange and coordinate information [Driskell and Salas, 1992; Shaw, 1932] identified two types of team members experimentally. It was shown that *egocentric* team members did not take the information of the partners into account in sequential binary decision tasks for dyads. This behavior led to poorer performance than those of *collectively oriented* team members.

Based on the results found in Driskell and Salas [1992] it is assumed that this additional channel of communication leads to increased performance. This idea founds further support in an experiment executed by Knoblich and Jordan [2003], where an experimental setup of a dyadic pursuit tracking task is used to understand anticipatory object control in interaction with a partner. In this setup participants did not have haptic feedback from their partner because they did not execute the linear movement of the virtual cursor in parallel. Instead, each of the partners had a different action to perform: one had to press a button responsible for the acceleration of the object, the other a button responsible for deceleration. The partners could not see each other or talk but in some conditions the partners had external feedback on what the partner is doing (auditory cues for pushes on the button). Performance increased with these auditory cues of the partners task execution. As proposed by the authors, the most likely reason for this is that with external cues the partner's actions can be integrated in ones own action plans. The idea that information from additional modalities (here vision) enhances verbal communication has been addressed experimentally by Gergle et al. [2004], too. Based on the approach that grounding is a key concept of communication (Clark and Brennan [1991]), i.e. that common ground / shared knowledge / shared mental models (all considered synonym here) simplifies communication Gergle et al. [2004] set up a dyadic puzzle experiment. They varied the amount of shared visual information. The more information was shared between partners, the higher was performance. This effect was stronger, when task complexity increased.

To summarize, it is so far unclear if mutual haptic feedback enhances intention negotiation, especially, if it leads to higher performance and to which costs such an improvement can be achieved. Thus, the usefulness of the haptic channel for collaborative scenarios cannot fully be answered by existing literature.

5.2 Efficiency in Low-Level Collaboration

In this subchapter low-level haptic collaboration is examined, where intentions have to be negotiated on *how* to move a jointly manipulated object. Herein, efficiency is investigated as a manner to relate task performance to the physical workload (effort), and thus, understand possible advantages of mutual haptic feedback in human collaboration.

Executing a joint tracking task (introduced in detail in Section 4.2), two human partners were asked to move a virtual object along a given reference path, which scrolled down on the two screen. The task was executed with two one-degree-of-freedom devices, compare Figure 5.2. The instructed desired trajectory is kept identical for both partners, so intention negotiation on where to move the object (high-level haptic collaboration) is not required.

In order to understand the effect of mutual haptic feedback in human haptic collaboration, an interactive condition with haptic feedback from the partner (*VH*) was contrasted to an interactive condition without such feedback (*V*), where haptic feedback was provided from the object only. It is important to note, that haptic feedback from the environment (here the object) is nonetheless given in this condition. Thus, difference between the two collaborative conditions are not influenced by a general advantage of haptic feedback but are related to the forms of intention negotiation provided: with only visual feedback from the partner, the inconsistencies between own movements and resulting object movements allow inferences on the partner's actions. In con-

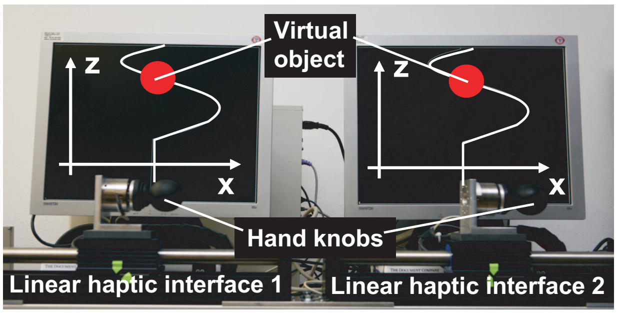


Figure 5.2: Photo of the experimental setup consisting of two linear haptic interfaces and two screens with the graphical representation of the tracking path. During experiments a wall was placed between the participants blocking the view on the other participant's screen.

trast, the partner's actions can be directly perceived if mutual haptic feedback is implemented. Furthermore, two "alone" conditions are used to analyze the effects of a partner and show how well the task is executed if intention negotiation is not required. As this efficiency analysis is focusing on physical workload, which depends on the inertia of the manipulated object, the interactive conditions are compared to an "alone"-condition where the same inertia has to be moved (*AF*) and one where only half of the inertia has to be manipulated (*AH*) (compare Section 4.2.4 for details).

After raising research questions on the efficiency of mutual haptic feedback in a task requiring intention negotiation within low-level haptic collaboration, details on the analysis of the above described experiment are given. Then, statistical results are reported and discussed in the end of this subchapter.

5.2.1 Research Questions

Most studies reported in literature suggest a performance advantage due to additional feedback from the partner, here, provided by mutual haptic feedback. The relation between the task performance and the accompanying physical effort has not been addressed experimentally so far.

Contrasting the experiments reported in literature, in the experiments presented in the following, the amount of exchanged information is not treated as result of interpersonal differences, which are balanced out within the sample as in [Driskell and Salas, 1992; Shaw, 1932], but is experimentally varied by the provided communication channel, i.e. whether there is mutual haptic feedback between partners or not. Even though, in these experiments verbal communication (as in Gergle et al. [2004]) is not allowed (in order to address the effects of haptic collaboration only), the mutual haptic feedback is additional information compared to visual information on the partner's motions. Therefore, when generalizing the results from Gergle et al. [2004] and Knoblich and Jordan [2003], it can be expected that additional information, as it is given with mutual haptic feedback, helps to establish common ground/shared action plans, and thus increases joint task performance. However, it is unclear to which extent these results can be generalized to haptic collaboration. Thus, there is not enough theoretical knowledge to raise concrete hypotheses here. Instead, the focus is on two research questions examined by an exploratory study:

- **RQ1 - Effect of mutual haptic feedback on efficiency:** Is haptic feedback from the partner efficient in collaborative trials where intention negotiation is only required to decide how to move the object? The mutual haptic feedback condition is compared with two control conditions: a) individual execution and b) interaction without this communication channel to understand this effect. This question combines the control conditions proposed by different studies in the literature overview (Section 5.1) in a single experiment. It is assumed that good performance results from good collaboration. The measured physical effort is an indication to which degree the haptic collaboration channel is used, as the effort for optimal task execution is controlled experimentally (via the adjusted inertia and equivalent paths). The efficiency measure relates performance and physical effort.
- **RQ2 - Efficiency distribution between partners [3]:** How is efficiency distributed between partners (within a dyad), comparing trials with and without mutual haptic feedback in low-level of haptic collaboration? This sub chapter focuses on the efficiency of interactive behavior in a task, where strategies on how to move the object have to be defined in a shared action plan. Thus, this question allows first insights into the differences in strategies when mutual haptic feedback is provided compared to the control condition.

5.2.2 Data Analysis

Participants

The shared tracking task experiment (for details see Section 4.2.4) was conducted with 24 participants (age mean: 27.6, std. deviation: 2.5) forming 12 independent mixed-gender dyads. [4] In the "alone"-conditions only one randomly selected partner of a dyad is analyzed to guarantee statistical independence of data points within this condition.

Measures

Efficiency is analyzed with the measure described in detail in Section 4.3.2. This measure relates performance to physical effort. For the efficiency analysis associated with the first research question, the relative *dyadic efficiency* measure (Λ_d^T) is used for all four conditions as a description of the *overall system* (whether it contains one or two humans, see Equation 4.21 for details). The root mean square error (RMS) is chosen as the performance measure with the goal to punish larger deviations from the desired trajectory harder. Because in this efficiency definition, performance values are positively defined, RMS is transformed to receive a positive measure (i.e. high values mean good performance) as follows:

$$B = 1 - \frac{RMS_j}{RMS_{max}} \tag{5.1}$$

[3] As performance in this jointly executed task is identical for both partners, difference in efficiency are only due to effort measures.

[4] For the sake of completeness it has to be mentioned that the 24 participants formed six groups of four persons each. Participants interacted in accordance with a round robin design (Kenny et al. [2006]), such that each performed in partnership with each of the group members as well as alone. In the results presented in this section, due to the assumptions in inference statistical analyses (Kenny et al. [2006]) *only independent dyads* were considered, i.e. each analyzed participant was part of only one dyad.

where RMS_{max} is the maximum RMS found in a given data set (here: maximum of the whole experimental data, $RMS_{max} = 0.0055m$) and RMS_j is the error of trial j.

Effort Γ_d can be expressed as power- (MAP) or force-based (MAF) measure. The focus here is on the first, as it is more representative for the *V* condition (for further argumentations on the use of a specific effort measures see Section 4.3.2).

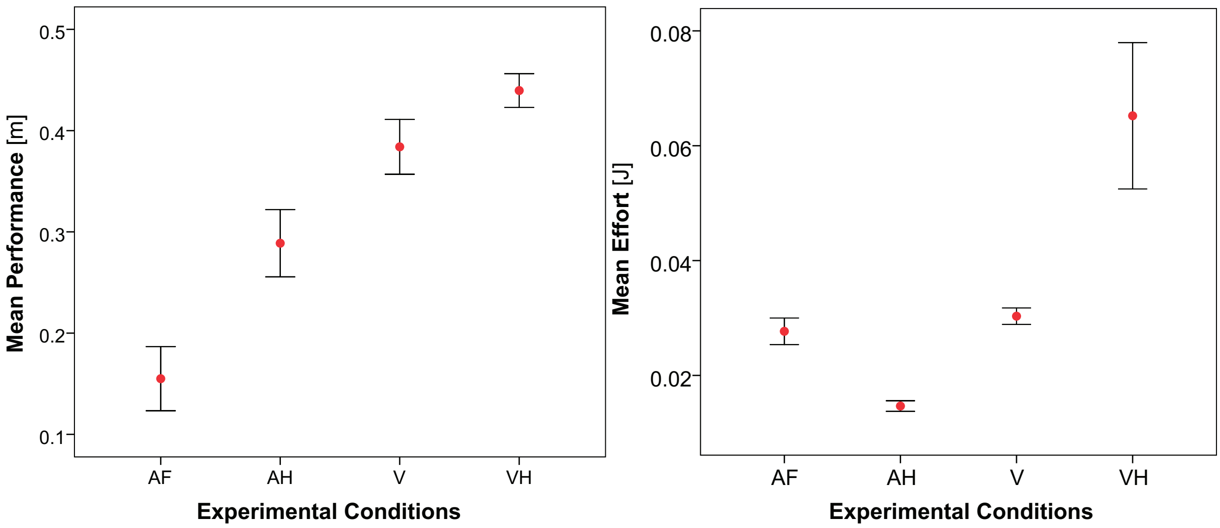
To compare the power-based effort in *"alone"* and *dyadic* trials it is necessary to define a *single measure for both cases*: MAP_d^T is a dyadic measure which is used in the "alone"-condition as well. In the "alone"-condition, the influence of the (nonexistent) partner is set to "0" ($MAP_d^T = MAP_{i1}^T + MAP_{i2}^T = MAP_{i1}^T + 0$). Thus, the efficiency measure Λ_d^T based on this overall effort measure can be used to describe all four experimental conditions. Both performance and effort are reported per trial. This leads to the efficiency measure:

$$\Lambda_d^T = \frac{Z(B) - Z(\Gamma_d)}{\sqrt{2}} \tag{5.2}$$

The z-standardization, $Z(B)$ and $Z(\Gamma_d)$, takes place over all experimental conditions.

To answer the second research question, it is required to approach *individual efficiency* Λ_i^T *within a dyad* (contrasting dyad members). This, of course, can only be examined in the interactive conditions. Here, efficiency has to be defined for a single partner rather than at the dyadic level: To define the former, the performance and the effort measure have to be described individually for both partners. Due to the fact that performance in the haptic task is described in relation to the object involved (i.e., it is the same measure for both partners), the efficiency varies between partners in relation to the effort measure only. The individual efficiency ($\Lambda_{1,i}^T$) is calculated correspondingly to the dyadic formula, but based on ($MAP_{1,i}^T$)and ($MAP_{2,i}^T$) for partner 1 and 2, respectively.

It is not possible to quantify the difference or similarity of the individual efficiency of dyad members with the Pearson correlation measure, because the two dyad members are exchangeable. Exchangeability here means, that there is no clear role distribution by which the individuals can be distinguished. For example, if we develop our data sheet for correlations, we build two columns, one for a certain variable of each partner. It is arbitrary if we allocate a particular individually measured efficiency to the column *partner 1* or *partner 2*. Thus, various possible groups of data can be built, leading to different correlations. One way to overcome this problem is the pairwise intraclass correlation (Griffin and Gonzalez [1995]; Kenny et al. [2006]), which can be based on the double entry method: all possible within-group pairings of scores are built before calculating the correlation on this dataset. For dyads, that means that the individual measures of a couple are entered in the dataset in both possible configurations. In this way the relation between the individual variables can be determined by a Pearson product-moment correlation. Based on this method, the intraclass correlations and the adjusted significance level from the doubled data entries (Griffin and Gonzalez [1995]) is calculated. The z-transformation of the efficiency-variable is conducted on the double entry data set across the data from both interactive conditions.



(a) Performance B **(b)** Effort MAP_d^T

Figure 5.3: Performance B is measured as positively transformed RMS (higher value = high performance). Effort is defined as mean absolute power per trial. Comparison between the four experimental conditions *AF* ("alone" with full mass), *AH* ("alone" with half mass), *V* (visual interactive = no mutual haptic feedback), *VH* (haptic interactive = mutual haptic feedback): mean and one standard error.

5.2.3 Results

This section presents the experimental results in relation to the research questions raised in the beginning of this subchapter.

RQ1 - Effect of mutual haptic feedback on efficiency

Descriptive results of the effect of the four conditions on effort, performance and efficiency are depicted in Figure 5.3 and Figure 5.4. A one-way, repeated-measurement ANOVA was conducted separately for each measure. Because of a lack of sphericity for the effort and efficiency measures, the corresponding ANOVAs were Greenhouse-Geisser corrected. The results for all three analyses are presented in Table 5.2. Given a significant main effect of the feedback factor on all three measures, pairwise comparisons between experimental levels were executed with Bonferroni adjusted post-hoc tests. Table 5.1 shows the descriptive statistics and the pairwise comparisons for each measure and condition.

Performance (measured as positively transformed RMS: B) is better in interactive trials (*V*, *VH*) than in individual trials (*AF*, *AH*), as the relevant post-hoc comparisons reach significance, as shown in Table 5.1. Hence, even in this haptic collaboration task, which can be done alone, the participants profited from interaction with a partner. This is true even when the interactive conditions are compared with the *AH* condition, where the mass was halved, thus instantiating optimal mass sharing between two partners. Despite the descriptive tendency that reducing the mass in individual performance conditions and providing mutual haptic feedback increases performance compared to *AF* and *V*, respectively, these tendencies do not reach significance.

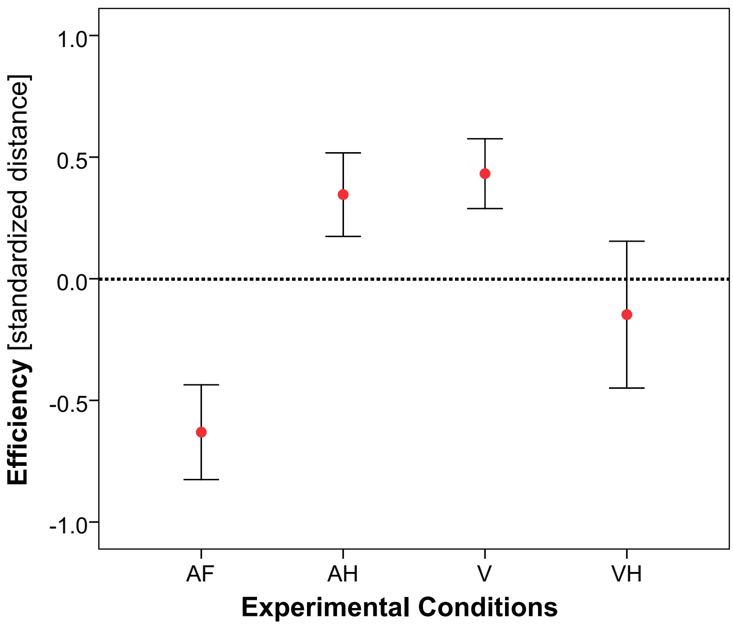


Figure 5.4: Efficiency Λ_d^T compared between the four experimental conditions *AF* ("alone" with full mass), *AH* ("alone" with half mass), *V* (visual interactive = no mutual haptic feedback), *VH* (haptic interactive = mutual haptic feedback): mean and one standard error. The horizontal line refers to the reference value of zero efficiency, representing average efficiency within the given sample, compare Figure 4.9.

Table 5.1: Descriptive results for the four conditions on performance (B), effort MAP_d^T and efficiency (Λ_d) and the pairwise comparisons. Significant comparisons on a 0.05 level are marked with *

Measure	Condition	Mean	Std. Deviation	AF	AH	V	VH
Performance	AF	0.155	0.110	-	0.052	0.001*	<0.001*
B	AH	0.289	0.033	0.052	-	0.028*	0.002*
	V	0.384	0.027	0.001*	0.028*	-	0.127
	VH	0.440	0.017	<0.001*	0.002*	0.127	-
Effort	AF	0.028	0.008	-	<0.001*	1.000	0.89
MAP_d^T	AH	0.015	0.003	<0.001*	-	<0.001*	0.013*
	V	0.030	0.005	1.000	<0.001*	-	0.077
	VH	0.065	0.044	0.89	0.013*	0.077	-
Efficiency	AF	-0.631	0.674	-	0.007*	0.005*	1.000
Λ_d^T	AH	0.346	0.595	0.007*	-	1.000	1.000
	V	0.432	0.498	0.005*	1.000	-	0.290
	VH	-0.147	1.045	1.000	1.000	0.290	-

Table 5.2: ANOVA results for the four conditions on performance B, effort Γ_d^T and efficiency Λ_d^T. Adjusted ANOVAs are Greenhouse-Geisser corrected

Measure	DoF	F	Sign.	partial Eta^2
Performance	3, 33	28.415	$<$0.001	0.721
adjusted Effort	1.051, 11.561	11.631	0.005	0.514
adjusted Efficiency	1.935, 21.281	6.671	0.006	0.378

Effort (Γ_d) is analyzed with the *power-based effort measure* MAP_d^T first, as it is considered more appropriate when analyzing the *V* condition, compare Section 4.3.2: The "alone" condition with the reduced mass elicits lower effort compared to the other conditions, which is due to the fact that here, the overall cursor mass is halved (10 kg) compared to all other conditions (20 kg). No significant difference is found between the effort in *AF*, *V* and *VH*. The mass that has to be moved (by either one or two humans) is equal in these conditions. That the effort between *V* and *AF* is identical suggests that no additional effort was necessary for interaction. Therefore, it is concluded that the effort is dependent on the mass rather than on the interaction, when no haptic feedback of the partner is provided. In the *VH* condition, however, the deviation from the mean effort values is much higher within the sample, this may be the reason why the descriptively higher effort in this condition does not reach significance, compared to *AF* and *V*. To examine the effort in the mutual haptic feedback condition in more detail, the *force-based effort measure* is applied in a second step. Note that, even though interactive forces can be measured in *V*, they are not felt by the participants. A descriptive comparison of the two respective force-based effort measures MAF_d^E and MAF_d^I is illustrated in Figure 5.5; descriptive statistics can be found in Table 5.3. The external forces, which are responsible for the object manipulation and hence, task execution, are comparable in both conditions. The interactive forces are not only increased in the *VH* condition compared to *V*, but also have a high variance. This allows the conclusion, that the high variance in the power-based effort measure MAP_d^T for the condition with mutual haptic feedback is due to the interactive forces.

Efficiency is analyzed by using the power-based effort measure only, corresponding to Equation (5.2). This allows considering the workload due to movement in addition to forces, which is more representative in the *V* condition. Efficiency is highest in the *V* and *AH* conditions, which do not differ statistically. That is, two people interacting with visual feedback (*V*) and 20 kg mass are as efficient in this task as one person performing with half the mass (*AH*). The comparable efficiency between these conditions reflects a trade-off: *V* requires higher effort but yields improved performance compared to *AH*. The efficiency for the *AF* condition is lowest and differs significantly from that of *V* and *AH*. The mean efficiency for the interactive haptic feedback condition *VH* lies between these two extremes and is not statistically different from any of the others. This means that with experimental power [5] in the current analysis, haptic feedback interaction is found neither to improve nor to worsen efficiency compared to other feedback conditions or doing the task alone. The finding that *VH*-efficiency does not significantly differ from *V*-efficiency is consistent with the previously described findings that mutual haptic feed-

[5] Power here means the capability of an analysis to detect differences in conditions. The power depends not only on the actual effect size (this difference) but also on the significance level, the sample size and the number of analyzed conditions

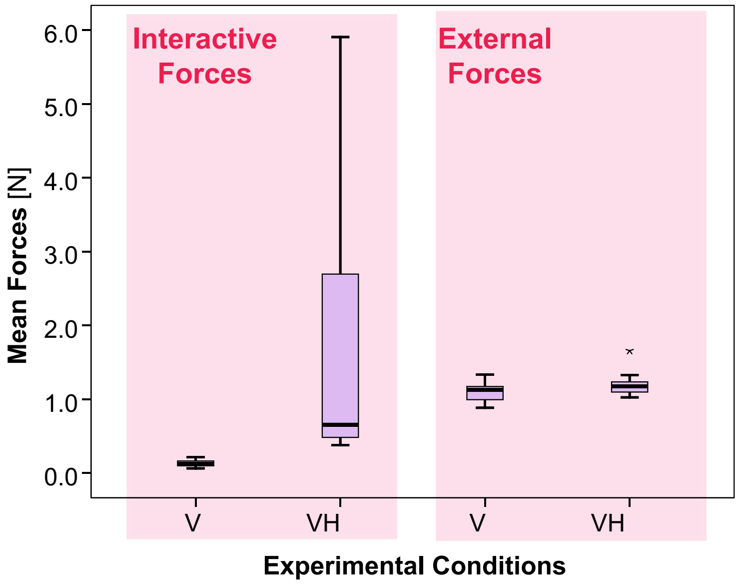


Figure 5.5: Box-whiskers-plot comparing external effort Γ_d^E and interaction effort Γ_d^I based on the force-based effort measures: mean absolute interactive forces and mean absolute external forces. Only the two interactive conditions are compared, as otherwise no interactive forces are involved in task execution.

Table 5.3: Mean and standard deviation of external effort MAF_d^E and interaction effort MAF_d^I for the two interactive conditions

Condition	Mean MAF_d^E	Std. Dev. MAF_d^E	Mean MAF_d^I	Std. Dev. MAF_d^I
V	1.102	0.135	0.130	0.049
VH	1.204	0.166	1.659	1.840

back neither improved performance nor required greater effort relative to interaction with vision alone.

RQ2 - Efficiency distribution between partners

In the aforementioned results efficiency was analyzed on a dyadic level. Now, it will be examined on an individual level and differences or similarities in this measure Λ_i^T between the two partners are compared. In Figure 5.6, the efficiency measure of each dyad member is plotted in relation to the partner. Each dyad is entered twice as proposed by Griffin and Gonzalez [2003], corresponding to the two columns in the double-entry data set. The closer the dots to the $45°$ diagonal, the more similar the dyad members are. The values of the intraclass correlations show that the efficiency of the two partners is generally very similar in both feedback conditions. Due to the rigid connection between partners the performance measures, on which these efficiency values are based, are equal for both partners. Corresponding, efficiency values differ between individuals within a dyad *only on the basis of the effort values*. The intraclass correlations on individual efficiency values within a dyad for the two interactive conditions are $V: r = 0.867; p_{one-tailed} = 0.002$ and $VH: r = 0.983; p_{one-tailed} < 0.001$, stating a high

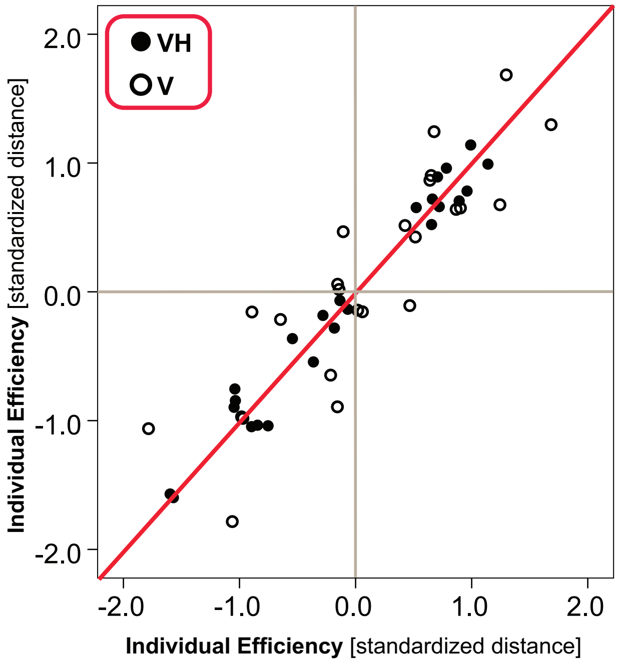


Figure 5.6: Similarity of individual efficiencies (Λ_i^T) *within* dyads. Each dyad is presented twice by a dot (based on the double entry method) The closer the mirrored dots are to the diagonal, the more similar the values of the two partners are . Differences in efficiency between the partners reflect differences in the applied effort, as the performance measure is equal for both partners in this task.

similarity between the two individual mean effort values, which lead to these efficiency values. The two intraclass correlations calculated for the two interactive conditions differ significantly from each other, when testing the hypothesis of equality with Fisher z-transformed values as proposed by Kenny et al. [2006] ($z = 2.3674; p_{two-tailed} = 0.018$). Taking into account Figure 5.6 this causes more similarity (closer to the $45°$ diagonal) between partners when mutual haptic feedback is provided.

5.2.4 Discussion

The presented analysis considered performance and effort as well as the relation between them, i.e. efficiency, in a low-level haptic collaboration task, where the desired object trajectory is identical for both partners. Thus, the results allow conclusions on the efficiency of providing mutual haptic feedback in tasks where individual intentions on how to move the object have to be integrated.

With respect to the **performance** measure, it can be stated that participants benefit from a partner. The advantages of interaction (which can e.g. be two sensory systems able to perceive errors faster reaction times allowed for by strategies of task sharing like acceleration-deceleration specializations between partners) outbalance the challenges related to intention negotiation. No difference in performance between the mutual haptic feedback condition compared to the interactive condition without such feedback was observed. Thus, the benefit of additional feedback from the partner found in other task [Gergle et al., 2004; Knoblich and Jordan, 2003] can not be reported here. One possible explanation may be the low complexity of the current task, which may have led to a ceiling effect here and could explain the different findings compared to other haptic collaboration Feth et al. [2009c].

It is not surprising, that the results reported by studies which compare haptic feedback from the partner and the object/environment to a none-haptic feedback condition [Basdogan et al., 2000; Glynn et al., 2001; Sallnäs et al., 2000; Sallnäs, 2001; Sallnäs and Zhai, 2003] are not repeated here. There, the focus was on the general effect on haptic feedback whereas here the effects of mutual haptic feedback as communication channel are examined by providing haptic feedback from the object in all conditions. Hence, it is possible that the performance advantage reported in previous studies is mainly due to the feedback perceived from the object, which may allow a higher general control of it. The current results, however, show that with the presented experimental setup, the haptic channel and its theoretical communication advantage does not increase performance in highly structured tasks where only intentions on how to move the object have to be negotiated.

The mutual haptic feedback condition requires most **effort**, measured as power, on the dyadic level. Striking is the high standard deviation in this condition. This variance is due to the high inter-dyadic differences in the mean interactive forces applied during task execution and not the external forces. Reasons for this differences are manifold. Personality variables and differences in capabilities to execute the task are considered the most important factors, which should be addressed in future research. As mentioned in Section 4.3.2, the effort measure is only defined for the static case, resulting in errors in this measurement due to the dynamic interaction. The differences in the found average behavior per condition are considered clear enough, to neglect this noise in the interpretation of results.

Turning to the measure of **efficiency**, the interactive condition without mutual haptic feedback led to increased efficiency relative to doing the task alone with full mass. However, when individuals performed in a half-mass condition, representing shared workload, their efficiency was equal to the vision-only interactive condition. Thus, as long as no haptic feedback was provided, the overall efficiency was influenced by the inertia of the object, rather than by the fact that the task was performed with a partner or not. When haptic feedback was brought into play, the mean efficiency tended to be lower than dyadic interaction using vision alone. The effect, however, was not statistically significant, given the variability in efficiency under haptic feedback. This in turn reflects the variance in interactive forces. Hence, the resulting efficiency values can be explained by the performance and effort results. Mutual haptic feedback cannot be considered as more efficient in the presented interaction task in general as it leads to higher effort without increasing performance. If there is intention negotiation between partners (on this lower level of haptic collaboration: strategies how to move the object) via the haptic channel, it does not pay off in better performance. One possible explanation is that the given task does not allow for a further increase due to haptic interaction because the maximum performance (considering the dynamics of the human action-perception system) is already achieved with visual-only feedback from the partner. Or, the task may have been too simple (it could be performed alone and was highly structured) to make an explicit negotiation of intentions necessary. In any case, mutual haptic feedback seems to be a hindrance rather than a support in the current task, in line with the suggestions from Reed and Peshkin [2008].

It is an open issue whether these results can be generalized to higher level haptic collaboration scenarios involving the negotiation of the shared trajectory in addition to the strategies as part of the joint action plan. Therefore, in the next section this topic is addressed by experimentally varying the amount of needed intention negotiation to accomplish the task. The complexity of the task is then increased as it now incorporates shared decision making, thereby representing higher level haptic collaboration.

The fact that the effort is distributed more fairly between partners when mutual haptic feedback is provided, may suggest a negation of strategies within the dyads. The shared action plan would then have the goal to share the task workload equally. Within the following chapter (subchapter 6.3), strategies on how to distribute forces applied on the object among dyad members are addressed more explicitly with a *dominance* measure.

5.3 Efficiency in Shared Decision Making (High-Level Collaboration)

In the previous subchapter, it was reported that mutual haptic feedback does not increase efficiency in a one DoF joint tracking task when intention negotiation is only required in relation to action plans dealing with *how* to move the object. This was due to the fact that performance was equal in both interactive conditions, with and without mutual haptic feedback, but interaction forces between partners were increased in the latter condition. These findings may be explained by the low task complexity, which did not allow for benefits of mutual haptic feedback in more challenging intention negotiation tasks. Therefore, in the current subchapter an effect of mutual haptic feedback on efficiency is investigated by experimentally controlling and increasing the need to negotiate intentions. The focus is on high-level haptic collaboration, where the negotiation of action plans does not only require to agree on a strategy *how* to move an object but additional requires decisions on the shared desired trajectory, i.e. *where* to move the object, compare Figure 5.1. To explicitly increase task complexity towards *haptic shared decision making* (HSDM), binary decision situations with different preferences on the two options for the individual partners are introduced.

Whenever the environment or capabilities of interacting partners (whether humans or robots) offer several action plans to achieve a shared goal, shared decision making plays a key-role. *Decision making* is generally defined as the act of choosing one available option out of several possibilities which may have different trade-offs between benefits and costs. Some researchers refer to decision as the “forming of intentions before acting” [Hardy-Vall?e, in press] whereas others define the exact point of time as decision [Hoffman and Yates, 2005]. In *shared decision making* two partners have to agree on a solution. Even though, they may prefer different action plans due to different information bases or perceived options. Shared decision making is the interactive process of negotiating action plans to reach the shared goal. Thus, shared decision making is one form of collaboration and allows to study intention recognition between partners i.e. the construction of a mental model of the partner’s decision state. For a general overview on shared decision making see Castellan [1993]. In Payne et al. [1993] it is assumed that an effort accuracy trade-off exists in decision making: people are assumed to be motivated to use as little effort as necessary to solve a decision problem. This theory can be directly investigated with the use of the efficiency measure. As a first step towards the realization of robotic partners, which are

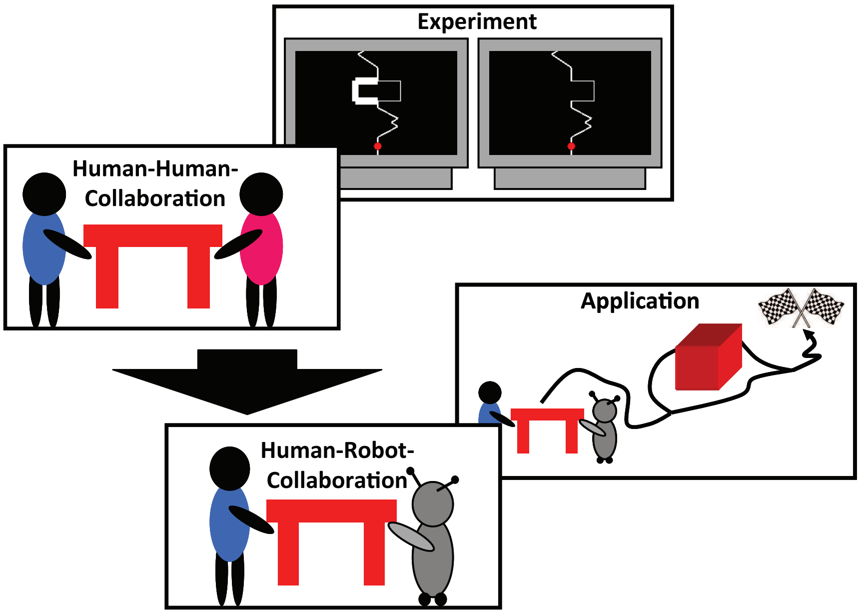


Figure 5.7: In line with the approach to learn from human dyads to enhance human-robot collaboration, this experiment investigates haptic collaboration of two human users with the shown setup including shared decision making.

able to show human-like behavior-patterns in haptic collaboration, the following study investigates the efficiency of intention negotiation via mutual haptic feedback in a task involving *haptic shared decision making* to find out, whether the process of shared decision making is actually enhanced by this additional modality available to transfer signals between partners. In line with the general approach followed in this thesis, collaboration between two humans is investigated to derive guidelines for robotic partners in VR, tele-presence and autonomous assistance robots.

Except for the decision situations the experimental design is identical with the one used in the previous study on efficiency in low-level haptic collaboration, compare Figure 5.7. Binary-shared decision-making in haptic collaboration has application in real-life scenarios as obstacle avoidance.

In the following hypotheses on the efficiency of mutual haptic feedback in a joint tracking task containing binary-shared decision-making are presented. Next, detailed information on the data analysis are given. Afterwards the results are presented. Their discussion is given in the last section of this subchapter.

5.3.1 Hypotheses

An interactive tracking task is executed by two human partners. It includes binary, shared decision situations. The effect of mutual haptic feedback on efficiency is addressed by comparing it to a control condition with haptic feedback from the object only. Three different types of decisions are contrasted (details see Figure 5.8): *A*) decisions where the experimentally instructed preferences of the two human partners on the two tracking path options are equivalent; *B*) decision types where only one partner has a preference whereas the other is undetermined; *C*) decisions where the preferences of the two partners are opposite. The need for negotiation between partners is expected to increase in the order of the presented decision types (representing an upward trend in task complexity, which is experimentally controlled). The following hypotheses are raised:

- **H1: Performance** decreases with an increase in the need for negotiation of intentions in *decision* situations (*A* to *C*). In addition, mutual haptic *feedback* should lead to higher performance (especially in decision type *C*, where the task is most challenging) because of the additional communication channel to negotiate on intentions.
- **H2: Effort** (measured as energy) is higher when *decision* preferences between partners are less compatible, expressing the negotiation activities. Furthermore, mutual haptic *feedback* is assumed to generally cost higher effort in accordance with the results reported in the previous subchapter and as an effect of the actual use of this channel for intention negotiation.
- **H3: Efficiency**, meaning the relation (within the given sample of participants) between performance and physical effort, is higher for *decision* types with low need of negotiation (type *A* and *B*) than in decision type *C*. This is expected because task execution should be easier and no effort is necessary for intention negotiation in the latter case. The relation of the assumed performance benefit from mutual haptic *feedback* compared to the effort costs cannot be predicted due to missing previous knowledge. Thus, the effect of mutual haptic feedback on efficiency is formulated as open research question.

5.3.2 Data Analysis

In the current analysis, only the two interactive conditions *VH* and *V* (with haptic feedback from the partner, and without, respectively) are compared. Focusing on *shared* decision making, the individual conditions loose their meaning in the current study. However, participants also conducted an “alone” condition containing binary decisions. This is mentioned for the sake of completeness and is not part of the analysis reported here. The two interactive conditions are the same as in the experiment on efficiency in low-level haptic collaboration (for details compare Section 4.2.4).

Participants

In this study, 58 participants (total of 29 dyads: five male, two female and 22 mixed dyads; mean age: 25,78 (standard deviation = 4,87)) are involved, extending the sample size on which the results reported in Groten et al. [2010] are based (a publication in relation to this subchapter). The tracking task including binary decisions was originally conducted by 32 participants forming eight groups of four persons each. Only independent dyads (16) were analyzed due to the independent error assumptions in inference statistical analyses (Kenny et al. [2006]). Here, this sample is increased by another 13 dyads. The reason is found in some interesting descriptive results which did not reach significance in the previous analysis but which may do so with the larger sample size.

Participants were informed about the feedback condition beforehand. In addition, they knew that the first curve of the tracking path was for practice and would be excluded from the analysis. Participants had an extended test run where they could view both screens and thus gathered

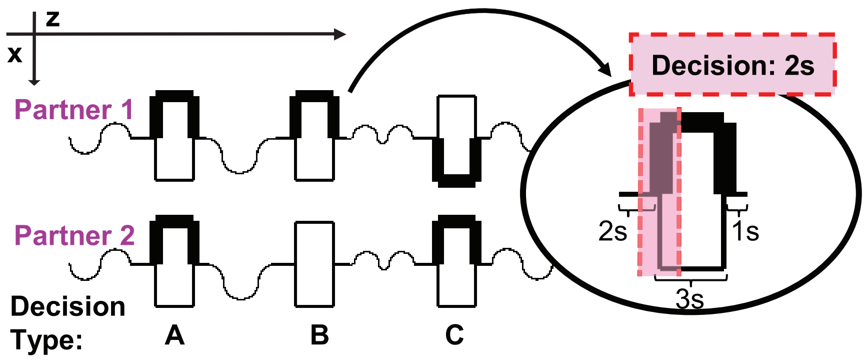


Figure 5.8: Exemplary paired reference tracks which "scroll down" the negative z-axis. In reality, the track is rotated by -90° compared to this picture, see also Figure 5.7. The instructed individual preferences (thickness of the path) are varied between partners to make action plan negotiation necessary. The enlarged section depicts which part of the decision is analyzed (2s). This is identical for all three decision types.

information on the different types of decision situations. Therefore, participants were aware of the fact that they had to negotiate intentions with the partner.

Analyzed Decision Types

The three decision types are depicted in Figure 5.8. Based on the assumption that a thicker path is preferred as it is easier to follow, the decision types are defined in the following:

- **Decision type A**: requires no negotiation of action plans as both partners prefer the same option (instructed via the individual path thickness).
- **Decision type B**: instructs a preference to only one partner. Negotiation of action plans may be necessary because it is unpredictable how the partner, who has no instructed preferences, may prefer to accomplish the task to stay on the track.
- **Decision type C**: The negotiation of the executed trajectory is inevitable, because opposite preferences are instructed to the partners.

To answer a possible side bias in decision situations, each decision type was presented in all possible left / right combinations. That leads to 8 analyzed decision situations (2 decision type *A* + 4 decision type *B* + 2 decision type *C*).

Summarizing, the experiment allows investigating two factors which may have an effect on the efficiency of interacting dyads in kinesthetic tasks: a) the three decision types, representing the need for trajectory negotiation and b) the presence of mutual haptic feedback. This results in a 2*3 fully crossed experimental design which was conducted as repeated-measurement study, meaning that all participants provided data for each of the six conditions. Whereas the decision types varied within one trial, the feedback conditions were investigated in different trials. Each trial was executed with one of eight different tracks. The tracks alter with respect to the presented order of the path sections including the eight analyzed decision types. In this way learning-effects through track repetition are prevented. In addition, the sequence in which the feedback conditions were presented to the participants were randomized .

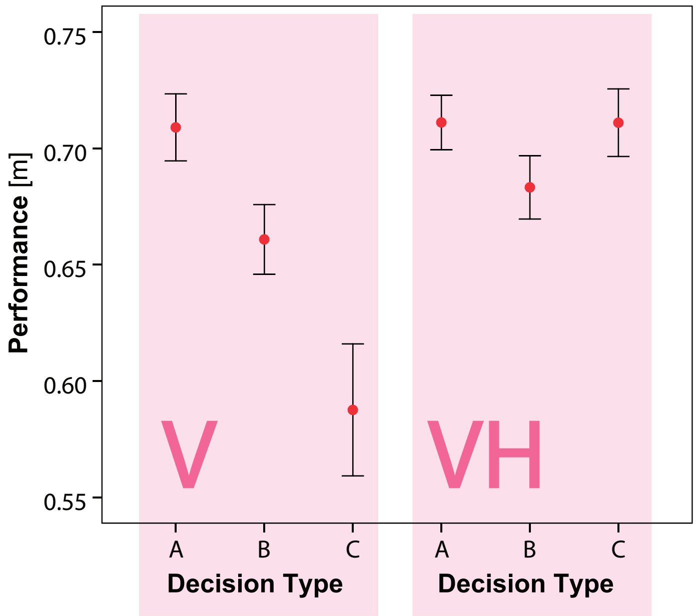


Figure 5.9: Mean and one standard error of performance measured as positively transformed RMS error (higher value = higher performance), contrasting the two feedback and three decision conditions. With mutual haptic feedback (*VH*) performance is higher compared to the control condition without such feedback (*V*).

Measures

In the current analysis the efficiency measure presented in Section 4.3.2 is used. This measure relates performance to physical effort.

Due to the dynamics of the human arm and negotiations on the executed shared trajectory, participants were not able to accurately follow the step in the path during decision situations. Therefore, performance, effort and the resulting efficiency are calculated in a two second interval around each decision (interval size defined by inspection), see Figure 5.8. The *z*-standardization of the performance and effort values to obtain the efficiency values took place across all decision types and repetitions as well as across both experimental conditions.

5.3.3 Results

H1: Performance

Descriptive results on performance are depicted in Figure 5.9. A 2(feedback)*3(decision type) repeated measurement ANOVA shows that performance is significantly influenced by the provided feedback (and thus possibilities to communicate) between partners ($F_{1,24} = 12.056; p = 0.002; \eta_p^2 = 0.334$): The positive performance measure (transformed root mean square error) is higher when mutual haptic feedback is provided. In addition, the decision type significantly affects performance ($F_{2,48} = 6.568; p = 0.003; \eta_p^2 = 0.215$): The mean performance across both feedback conditions is lower with higher complexity in decision types. Hypothesis 1 is strengthened. However, only decision type *A* is significantly different from the other two (*A* vs. *B*: p = 0.035; *A* vs. *C*: p = 0.006), whereas there is no significant difference between decision type

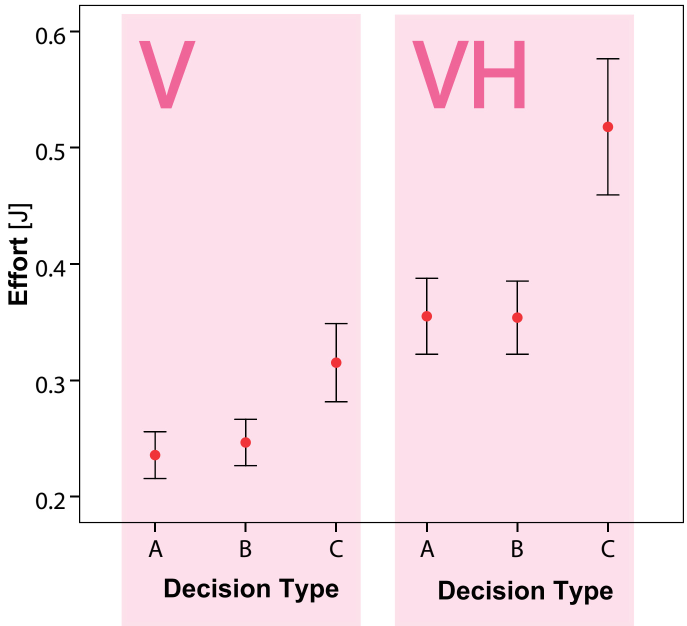


Figure 5.10: Mean and standard error of effort values (measured as MAP^T) contrasting the two feedback and three decision conditions: Increased decision complexity leads higher effort. With reciprocal haptic feedback (*VH*) effort is increased compared to the control condition without such feedback (*V*).

B and *C* (p = 0.721) as tested with Bonferroni adjusted pairwise comparisons. Figure 5.9 illustrates that the need to negotiate a decision with a partner negatively influences performance with "vision-only" feedback from the partner. If mutual haptic feedback is provided the performance stays more stable. This interaction between the two factors reaches significance (Greenhouse-Geisser corrected due to a lack of sphericity: $F_{1.374,32.340} = 12.085; p = 0.001; \eta_p^2 = 0.334$). The stable performance suggests that intention negotiation can take place via mutual haptic feedback as otherwise a decrease in performance would be expected with higher need to negotiate intentions. Judging from the effect size (η_p^2), feedback has a higher influence on performance than the decision type.

H2: Effort

Effort results are shown in Figure 5.10. Descriptively effort is higher with mutual haptic feedback and is highest within each feedback condition for decision type *C*. Effort is again analyzed with a 2(feedback)*3(decision type) repeated measurement ANOVA. Results support the descriptive findings: effort is significantly affected by the feedback factor ($F_{1,24} = 22.352; p < 0.001; \eta_p^2 = 0.482$). Furthermore, the effort significantly increases when the involved preferences in the decision types are opposite, meaning that the effort in decision type C is significantly higher than in the other two decision types (Greenhouse-Geisser corrected due to a lack of sphericity: $F_{1.391,33.379} = 16.799; p < 0.001; \eta_p^2 = 0.412$; Bonferroni adjusted pairwise comparisons: *A* vs. *B*: p = 1.000; *B* vs. *C*: p $<$ 0.001 and *A* vs. *C*: p $<$ 0.001). Hypothesis two can be assumed to be correct for the given task. The effect of the two factors on effort is similar as can be seen from the effect size (partial η^2), interaction between factors is not significant. As the necessary effort to execute the task is equal in all six experimental cells (resulting form fully

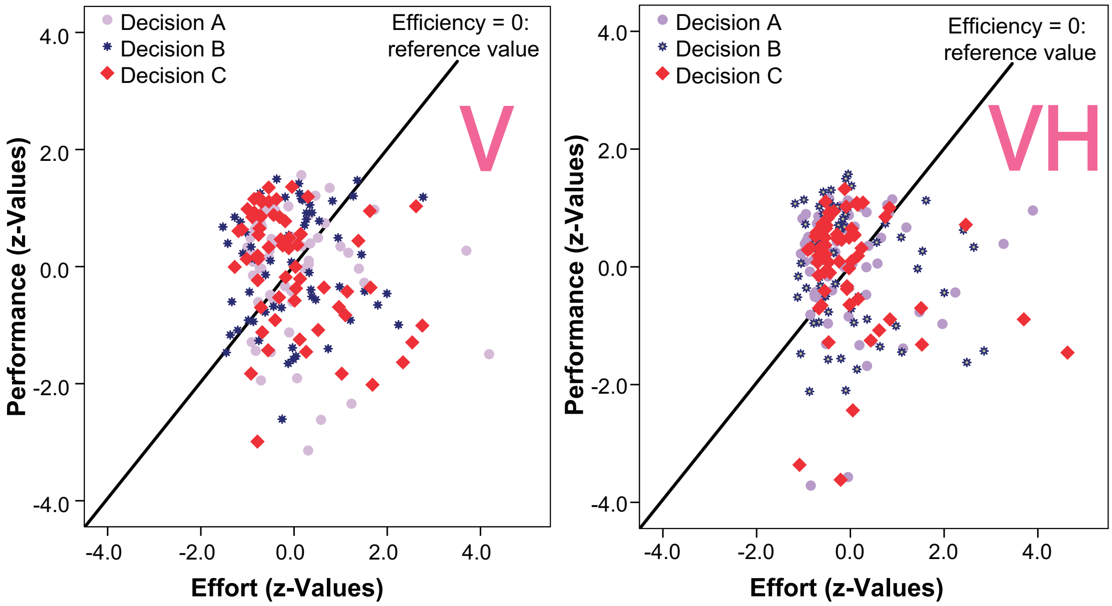


Figure 5.11: Scatter plots showing the efficiency values resulting from z-standardized performance and effort separately for the two feedback conditions. The three different decision types are color-coded. The zero of each axis represents the mean of the z-standardized values across all conditions. Efficiency is calculated as distance from the diagonal reference line which represents an efficiency value of 0, representing average efficiency. Positive/negative efficiency values describe efficient/inefficient behavior.

crossing the two factors), any additional effort is related to interaction between partners. Effort increases with the need to negotiate intentions comparing conditions *A* and *B* to *C*.

H3: Efficiency

Efficiency values are depicted in Figure 5.11, which shows scatter plots visualizing the calculation of dyadic efficiency values based on the z-standardized performance and effort values. Results are depicted separately for the control condition without haptic feedback between partner (*V*, left side in plot) and the mutual haptic feedback condition (*VH*, right side). The zero line of each axis presents the mean of the z-standardized values across all conditions. Even though, for the latter condition a larger amount of values is above the reference line (zero efficiency) than for the control condition, the descriptive differences between the two conditions are low.

In Figure 5.12 the means of these efficiency values per condition are shown. The reference value of zero efficiency is depicted as horizontal line here. A 2(feedback)*3(decision type) repeated measurement ANOVA reveals no evidence that the feedback factor is influencing efficiency. Thus, the research question related to hypothesis three can be answered by reporting that there is no effect: The linear relationship between effort and performance is similar for both feedback conditions across all decision types. Efficiency values are affected by decision type (Greenhouse-Geisser corrected due to a lack of sphericity: $F_{1.344,32.247} = 15.919; p < 0.001; \eta_p^2 = 0.399$. Bonferroni adjusted pairwise comparisons show that all decision types lead to significantly different efficiency values (*A* vs *B*: p = 0.035; *B* vs. *C*: p < 0.001; *B* vs. *C*: p

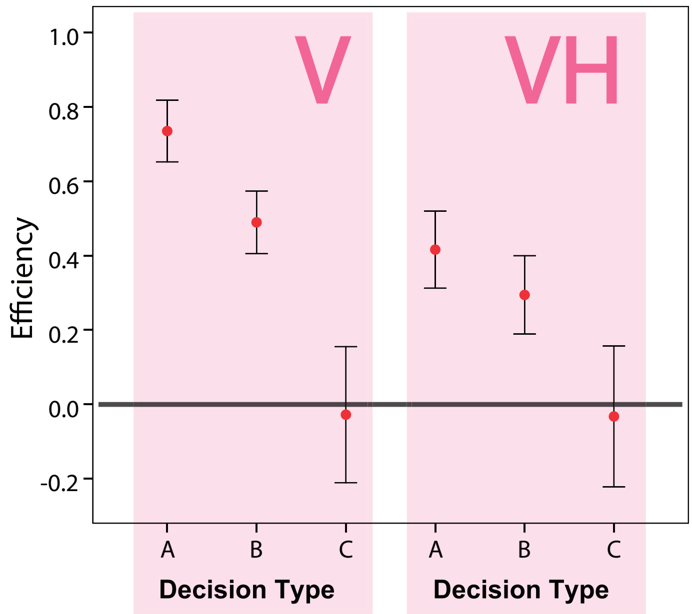


Figure 5.12: Efficiency measure depending on the feedback (*VH* and *V*) and decision type factor (*A*, *B*, *C*): mean and standard error. The horizontal line is the reference value of zero efficiency, expressing the linear mapping of z-standardized performance and z-standardized effort within the given sample. Only the decision factor had significant influence on efficiency: With increased need to negotiate intentions in decisions, the efficiency decreased.

= 0.017). Efficiency decreases with the need to negotiate intentions in decision situations. The lower this need is, the higher performance and effort needed to negotiate are, resulting in high efficiency for decision type A and low efficiency for decision type *C*.

5.3.4 Discussion

In the following the results from an efficiency analysis relating performance and effort measures are discussed. The haptic collaboration task in this experiment was designed to investigate high-level haptic collaboration including shared decision making. The effects of two factors where examined: the presence of mutual haptic feedback and the need to negotiate intentions in decision situations.

From Gergle et al. [2004] and Knoblich and Jordan [2003] it was expected that the additional source of information on the partner's behavior additional information as it is given with mutual haptic feedback, increases joint task performance. This can be support by the presented results: Performance is higher with mutual haptic feedback than without, averaged across the decision types. In average, across the two feedback conditions, performance decreases with the need of intention negotiation between partners. However, the significant statistical interaction tells us that performance is more stable with mutual haptic feedback across the decision situations when the need to negotiate intentions increases.

Across all decision types, the effort with mutual haptic feedback is higher compared to the vision control condition. It was shown that with opposite preferences between partners in decision situations (highest need of intention negotiation within the three decision types) the amount of physical effort is highest, which is interpreted as additional negotiation effort. This is equally true for both feedback conditions.

Overall, a higher need to negotiate between partners leads to more inefficient behavior: Increasing task challenge results a) in higher effort, especially for the mutual haptic feedback condition and b) in lower performance in the vision condition. As the efficiency measure relates those two components, the resulting overall (across decision types) efficiency for the two feedback conditions is comparable. The additional effort related to reciprocal haptic feedback pays off with better performance which is in line with "protection of performance" by the allocation of further resources, which is predicted by the cognitive-energetical framework introduced by Robert and Hockey [1997] and the trade-off described by Payne et al. [1993] (see Section 5.1).

Based on the findings in this experiment the following conclusions on mutual intention negotiation via mutual haptic feedback can be drawn: The higher effort in the mutual haptic feedback condition compared to the control condition shows that there are forces exchanged between partners in excess to those needed to move the object task-optimal (which required the same forces in both conditions). However, this does not necessarily imply that intention negotiation takes place via these signals. Performance is considered as an indicator for communication via the haptic channel. It is assumed that when keeping factors such as haptic feedback from the object comparable, variations in performance between the two feedback conditions have to be caused by either a better negotiation of action plans between partners (communication via the added haptic modality) or so far unknown additional advantages of mutual haptic feedback. An examples for such unknown advantages may be found in the "contradictory forces" between the dyad members, which were not task related, were examined and assumed to serve as increased stiffness (comparable to muscle contractions) with the goal to deal with perturbations. In the related study by Reed and Peshkin [2008], this hypothesis was not strengthened. Another advantage of haptic feedback may lay in the consistency between proprioceptive and visual feedback from the object position, which is not necessarily the case in the *V* condition Section 4.2. However, if such factors cause the performance benefits found when mutual haptic feedback is provided, a decrease in performance with higher need of negotiation would still be expected because those advantages would not simplify the complexity of shared decision situations. But, the performance with mutual haptic feedback is stable across decision types with increasing need for intention negotiation. Therefore, the first explanation, the actual use of the haptic channel to negotiate the shared action plan finds support. These findings justify further research on this modality in haptic collaboration and show that it is not arbitrary which force and motion signals are exchanged between human and robotic partners, requiring consideration in the design processes.

5.4 Conclusion

5.4.1 Summary

This chapter addressed the question as to what extent intention negotiation between two partners in a haptic collaboration task is possible via mutual haptic feedback. In a first attempt, an experiment was conducted which required intention negotiation only on the lower level of haptic collaboration, meaning that strategies on how to move the object had to be found. In a second study including binary decision making, high-level haptic collaboration was examined. Thus, this study additionally includes intention negotiation on where to move the object. In both experiments the effect of mutual haptic feedback was addressed by contrasting a condition where this feedback was provided to one where feedback was only provided from the object. The influence of mutual haptic feedback was measured in task performance, and the physical effort required for task execution, as well as efficiency, which combines these two measures.

For low-level haptic collaboration, it was shown that mutual haptic feedback does not significantly increase performance compared to a condition without such feedback. Combined with increased effort for the mutual haptic feedback condition, this feedback from the partner does not result in efficient task execution. However, it led to a fairer effort distribution between partners. For high-level haptic collaboration efficiency of mutual haptic feedback is again comparable to that of the control condition without such feedback. However, performance with mutual haptic feedback is higher. This benefit is achieved by the application of higher effort. The necessary effort to keep performance constant increases as the challenges of intention negotiation on the shared trajectory become higher. Together with the fact that without mutual haptic feedback performance decreases with the increase in negotiation necessity, it is concluded that mutual haptic feedback can be a valuable channel for intention negotiation in joint kinesthetic tasks.

The presented results are based on individual mean measurements per interaction and it is unknown if they hold beyond the given task. However, for the first time, evidence for the existence of "haptic communication" is reported. The results clearly justify further effort in investigating mutual haptic feedback, especially for tasks of higher complexity.

5.4.2 Future Work

In future, task complexity can be investigated further (e.g. object size and dynamics, degrees of freedom in individual movements, different tasks) as an influence factor on the relation between effort and performance in haptic tasks. Furthermore, cognitive in addition to physical effort could be addressed in haptic collaboration to obtain deeper insights into the costs of collaboration.

Investigating haptic collaboration over time may enable an identification of signals relevant for intention negotiation. Especially, it may allow insights on *how* intention negotiation takes place. This will be of importance when defining the range of signals which can be executed by robotic partners without risking misinterpretation by a human user. Time series analysis and information-theoretic approaches seem to be promising as e.g. proposed by Schreiber [2000]. One way to address the communication via the haptic channel further could be the explicit manipulation of the reliability of information transfer by experimentally controlling the physical connection between partners.

The effect of mutual haptic feedback was investigated by comparing this condition to one where no haptic feedback between partners was exchanged. In future, the efficiency measure can be employed to investigate differences between human-like and non-human-like haptic feedback as provided by artificial partners. This way the significance of human-like behavior can be understood further. As a first attempt in this matter compare Feth et al. [(submitted].

Because the results show that humans negotiate intentions in shared decision situations via mutual haptic feedback, the described experimental setup could serve as a tool to understand more about human collaboration in general. Social science is traditionally dominated by subjective data (e.g. from questionnaires after a social interaction). However, the experiments presented here may allow enhancement these measures by the recording of high sample rate behavioral data to investigate generic rules of human interaction behavior when the development of shared action plans is required.

5.4.3 Design Guidelines for Robotic Partners

As most tasks in real-life applications request a performance-optimal behavior, the results found in the second study advise the implementation of mutual haptic feedback. The analyses have compared mutual haptic feedback as exchanged between human partners with a condition without haptic feedback between partners. The results indicate conclusions for virtual reality applications where these two forms of feedback can be implemented: The fact, that humans are capable of negotiating intentions via haptic feedback does imply that human-like feedback is also worthwhile in other human-robot collaboration scenarios where the alternative would be to provide non-human-like feedback. Even if the robot does not transfer human-like haptic feedback to the human partner, attention should be paid to its actions as the resulting force and motion signals may still be interpreted as intentions by the human partner. The advantages of human-like haptic feedback in contrast to these alternatives should be subject to future studies.

The first experiment revealed that the effort distribution between partners is more balanced for both partners with mutual haptic feedback than in a vision-only partner feedback condition as was shown from the individual efficiency analysis. This suggests that haptic feedback should be implemented if the goal is a fairer effort distribution between partners. However, this may not necessarily be advantageous in any human robot interaction scenario, as the robotic partner could be defined as the partner carrying most physical effort. The next chapter addresses this topic more explicitly as dominance distribution between partners.

Altogether, the results found provide a motivation for further engineering effort to overcome stability challenges related to the implementation of mutual haptic feedback.

6 Shared Actions: a Dominance Analysis

In general, collaboration between two partners requires that they develop a shared action plan towards the task goal (shared intentions). Such a shared action plan has to define how the individual actions are integrated task-oriented. Especially in collaborations where a continuous interaction takes place, dominance distributions between partners are a prominent concept when describing action integration. Therefore, intuitive haptic human-robot collaboration should consider the distribution of dominance between partners: It is claimed that the dominance behavior measured when two human users collaborate can inspire dominance behavior of a robotic partner collaborating in a kinesthetic task. However, little is known about the dominance behavior humans show in haptic collaboration.

Thus, this chapter investigates dominance distributions between two human users experimentally as a first attempt to learn about the integration of individual action plans. In two subchapters, dominance is addressed separately for the two levels of haptic collaboration (as introduced in the haptic collaboration framework, compare Chapter 2) by experimentally controlling the intentions, which have to be negotiated between partners distinguishing between two dominance types, see Figure 6.1: In the lower level of haptic collaboration intentions on *how* to move an object along a desired trajectory towards a goal have to be negotiated by the partners. *Physical* dominance measures the distribution of applied forces for object-acceleration between partners in this context. High-level haptic collaboration including shared decisions on the desired trajectory additionally requires shared intentions on *where* to move an object. *Cognitive* dominance is used to measure the extent to which decision situations are dominated by a partner.

In contrast to the state of the art, which can so far only provide qualitative statements on dominance behavior in haptic collaboration, explicit intervals for both types of dominance behavior executed by human dyads are reported in this chapter. For the first time, it is investigated to what extend the distribution of physical dominance between partners changes across collaborations with different partners[1]. The influence of dominance differences on performance is studied. Furthermore, the relation between physical dominance before shared decision situations and cognitive dominance in these decision situations is modeled. No equivalent attempts to predict human behavior in haptic shared decision making can be found in the state of the art.

After an overview on related literature is given, two experimental studies on dominance differences shown by collaborating humans in a joint haptic manipulation task are presented. The chapter ends with a general conclusion including design guidelines for robotic partners in terms of dominance in collaborative haptic tasks.

[1] However, the results reported on physical dominance have been published in part by the author of this thesis in Groten et al. [2009a]

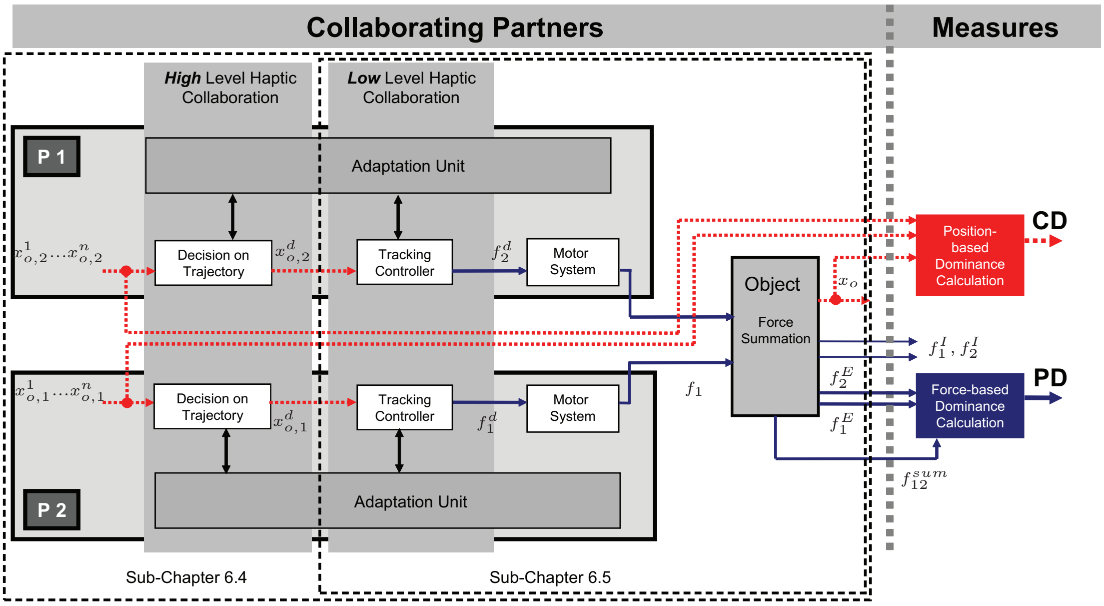


Figure 6.1: The figure shows two collaborating partners (P1 and P2), who jointly manipulate an object, in a simplified illustration of the framework introduced in Chapter 2. Signal flows relevant for dominance measures are depicted (for details see Section 4.3.3). The force-based measure *PD* refers to physical dominance addressed in Subchapter 6.4, and the position based measure *CD* to cognitive dominance addressed in Subchapter 6.3, and .

6.1 Dominance Definitions

Dominance can be defined as follows: It "refers to context- and relationship-dependent interaction patterns in which one actor's assertion of control is met by acquiescence from another" [Rogers-Millar and Millar, 1979] and is described as "a relational, behavioral, and interaction state that reflects the actual achievement of influence or control over another via communicative actions" [Burgoon et al., 1998]. It is important to note that dominance is a dyadic variable and hence is only present in interaction (unlike domineeringness, which is a character-trait and hence, an individual variable). Dominance complementarity therefore implies that when one partner is dominant to a certain amount, the other one is non-dominant by the same amount [Tiedens et al., 2007]. In Burgoon and Dunbar [2000] and Mast and Hall [2003] it is emphasized that dominance is a function of individual characteristics and situational effects, especially the specific relationship between the two partners.

These definitions of dominance are transferred to the two concepts of dominance in haptic collaboration as follows:

- *Physical* dominance: the relative (compared to the partner) amount of external force (responsible for object acceleration) applied to the jointly manipulated object, leading to a control over the trajectory in space.

- *Cognitive* dominance: the relative control over the jointly desired trajectory in decision situations, in the case where several object trajectories are possible.

6.2 Literature Overview

Physical dominance plays an important role in haptic collaboration as the actual object trajectory is directly influenced by the forces applied by the two partners. In the following a overview on literature related to physical dominance is presented:

Some approaches in haptic human-robot interaction focused on implementing robots as *passive* followers, e.g. Arai et al. [2000]; Hirata et al. [2002]; Kosuge and Hirata [2004]; Y. Hirata et al. [2010]. This, however, does not lead to real interaction because the two involved systems do not influence each other mutually. The same holds when the robot is the leader by replaying a prerecorded trajectory (Bayart et al. [2005]), which means *absolute dominance* [2] of the robot. These two approaches represent the extreme cases of physical dominance in haptic collaboration. More recent research in HRI addresses shared physical dominance in *interactive* scenarios to allow more intuitive interaction. Even though a theoretical physical dominance parameter has been used in control architectures (e.g. the α-parameter in Evrard and Kheddar [2009]; Khademian and Hashtrudi-Zaad [2007a,b, 2009a,b]; Nudehi et al. [2005]; Oguz et al. [2010]), only few studies empirically investigated physical dominance in human behavior in a haptic interaction task to gain reference values for designing robotic partners (Rahman et al. [2002a]; Reed et al. [2005]). In the following, experiments are summarized which examine human physical dominance behavior. Herein, two different types of studies are distinguished: Experiments which investigate human dyads, and experiments which address human-robot interaction.

To the author's best knowledge only two studies address physical dominance in haptic human-human behavior without manipulating the dominance distribution: An interactive one DoF pointing task was applied by Rahman et al. [2002a] and showed that one partner within a dyad can be characterized as leader and the other as follower. These results are based on a correlation analyses between the individually applied forces and the resulting object acceleration. Thus, the results allow no statement on the actual amount of dominance, i.e. the distribution of object control between partners. No correlation between dominance and performance was studied. In another study on human dyads conducted by Reed et al. [2005], a measure is introduced which describes the individual contribution of one partner (out of a human dyad, HHI) on the object movement in tasks, where forces are only applied in the same direction. Based on the average individual contribution (which is interpreted as physical dominance here) the authors derive the conclusion that some, though not all, dyads show specialized behavior, meaning that the individual contribution, and thus dominance of one partner, is higher in some phases of collaboration than in others.

Several studies address dominance in technically mediated setups which allow an experimental control of the dominance distribution: In Evrard and Kheddar [2009] collaboration between a virtual partner and a human partner jointly lifting an object across an obstacle was examined. A specialization in strategies was expected corresponding to Reed et al. [2005]. Different controllers were implemented for the virtual partner to provide haptic input of different dominance: the technical partner was leading, following or switching once or twice between those two physical dominance behaviors. However, the resulting force trajectories of both partners (the virtual and the human partner) did not show specialization, i.e. adaptation to each other. The contradic-

[2] which is intuitively accessible, however, cannot be measured with the physical dominance measure proposed in this thesis which assumes partners who are willing to collaborate

tion to the results presented by Reed et al. [2005] is explained by the higher task complexity in the experiment reported in Evrard and Kheddar [2009]. It has to be pointed out that according to the definition of dominance given above, the study published by Evrard and Kheddar [2009] investigates domineeringness rather than dominance: the dominance parameter responsible for the avatar behavior is determined before the actual collaboration, such not a result of interaction but a "character trait" of the avatar. The physical dominance factor which is implemented in the control architecture in Khademian and Hashtrudi-Zaad [2007a,b] is not based on empirical findings. However, in Khademian and Hashtrudi-Zaad [2007a] the effect of α on performance in a 2 DoF trainer/trainee tracking task scenario (HHI) was investigated. For the six participants acting as trainees, performance increased when a dominance value between 0.25 and 0.75 was given (where 0 and 1 are the extreme values of this complementary parameter). These findings further emphasize the necessity to develop technical partners, which are neither designed to passively follow nor to pure replay. Humans seem to perform better with shared dominance. In an experiment conducted by Oguz et al. [2010], two assistance functions and a no-guidance control condition were evaluated in a virtual game played by one human. A ball had to be moved in a plane where several targets in form of cylinders are given. The cylinder, which served as the current target, changed color. Thus, the other potential targets could be seen as obstacles. Therefore, this study can be seen as the only study where **cognitive dominance** could be of relevance, as a decision on the trajectories around the obstacles needed to be taken. However, the assistance functions were designed in a way that the partners either had equal control of the ball position or that the assistance function was adaptive in the way that it reduces its dominance "if the user and the controller have discordant preferences". Thus, the cognitive control is per definition with the participants and not the assistance function, and no subject of investigation. It could be shown that with a technical partner who adapts its dominance towards the user (based on variations in force parameters between the current interactive task and "alone behavior" of the participant recorded earlier), performance did not increase. However, the technical partner was rated more human-like in this case.

To summarize, it can be stated that humans seem to work with a physical dominance difference, leading to distinguishable leader or follower roles. However, so far no precise values of physical dominance in human-human collaboration are reported. The results concerning a correlation between dominance distribution and performance are contradictory: In Oguz et al. [2010]; Rahman et al. [2002a] no relationship between the two measures was found, whereas Khademian and Hashtrudi-Zaad [2007a] report a performance increase with shared dominance. So far, an analysis of cognitive dominance (decisions on object trajectories) is not yet reported in literature.

6.3 Physical Dominance (Low-Level Collaboration)

This subchapter reports the results of an experiment investigating *physical* dominance of human parters' behavior in a joint object manipulation task. Due to the fact that the theoretical knowledge on dominance differences in haptic tasks is limited, the experiment is conducted as an exploratory study. As the focus is on physical dominance, low-level haptic collaboration is studied with a jointly executed tracking task, where the instructed desired trajectories are identical for both partners, thus, no decisions on where to move (high-level haptic collaboration) are

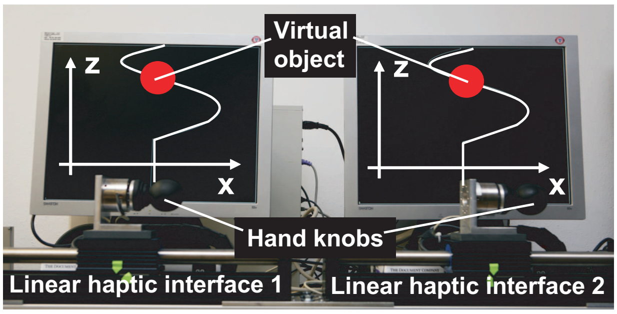


Figure 6.2: Photo of the experimental setup consisting of two linear haptic interfaces and two screens with the graphical representation of the tracking path. During experiments a wall was placed between the participants blocking the view on the other participant's screen.

involved in the shared action plans. The experimental setup is depicted in Figure 6.2: The cursor representing a virtual object has to be moved along the reference trajectory, which scrolls down automatically. Thus, the task is executed by one-dimensional movements along the y-axis only. For details on the experimental design see Section 4.2.4.

As this subchapter focuses exclusively on physical dominance (PD), it is always referred to this type when talking about dominance. The next section defines the research questions. Then, the experimentally gained data and its analysis are described. Afterwards, results are presented and discussed.

6.3.1 Research Questions

The following research question are addressed by the following analyses:

- **RQ1 - Physical Dominance Distribution:** Which physical dominance differences can be found in the behavior of two human partners executing a collaborative haptic task?

- **RQ2 - Physical Dominance and Performance:** Which physical dominance differences lead to high performance?

- **RQ3 - Consistency of Physical Dominance across Partners:** How consistent are physical dominance differences between human partners across several partners and sub-trials? The gained knowledge will give hints on the required amount of dominance adaptability of a robotic partner.

In order to gain information about the role of the haptic communication channel on dominance, a mutual haptic feedback condition (*VH*) is compared with a condition without such feedback, called vision condition (*V*), where only haptic feedback form the virtual object, which has to be moved along the reference path, is given.

6.3.2 Data Analysis

Participants

The analysis of dominance is based on 24 participants (age M: 27.6, sd: 2.5, 12 males) forming six groups of four persons each [3]. Participants interacted in accordance with a round robin design [Kenny et al., 2006], such that each participant performed the task with every group member. All participants were randomly assigned to a group. Due to the small strength necessary to collaborate in this task it is assumed that the physical strength of participants does not interfere with the results.

Measures

For the analysis of the experimentally gained behavior data, the physical dominance measure based on the ratio of individual external forces (forces that accelerate the object, thus are related to the control over the object) and the summed applied forces is employed (details in Section 4.3.3):

$$PD_{12,t} = \frac{f^E_{1,t}}{f_{sum,t}} \tag{6.1}$$

where $PD_{12,t}$ is the individual dominance of partner 1 over partner 2 and the index t the analyzed time point. The measure is force-based and describes the individual contribution to the object motion.

In order to analyze the effect of haptic feedback on the average dominance difference across the whole trial (RQ1), trials with and without mutual haptic feedback from the partner are considered (two conditions). The data analysis is based on the mean *dyadic* physical dominance difference measure ($\bar{P}D_{diff} = \left|\bar{P}D_{12} - \bar{P}D_{21}\right|$) per trial, where $\bar{P}D_{12}$ and $barPD_{21}$ are the individual means per analyzed interaction sequence. By taking the difference measure the problem that the mean of the individual dominance values for the two partners is 0.5 per definition can be overcome. The analysis of $\bar{P}D_{diff}$ is conducted using 12 mixed-gender dyads from the given dataset, which are independent (meaning that an individual is part of only one dyad). The same physical dominance measure and the same sample of 12 dyads are considered when addressing research question two. In addition, the Euclidean distance between the cursor and the reference track is used to quantify task performance. It is measured as root mean square error RMS to provide statements on the performance across a whole condition (see also Section 4.3.2).

To address the necessary adaptability of a potential robotic partner towards the human user's dominance, a method to describe the empirically found consistency of human physical dominance behavior across different partners is required. Such a method was found in the social relations model (SRM, introduced in Bond and Lashley [1996]; David A. Kenny [1996]; Kenny et al. [2001, 2006] in the context of social psychology). This method is related to multi-level linear regression, also known as hierarchical linear modeling as it introduces random coefficients to the regression model [Gelman and Hill, 2008; Snijeders and Kenny, 2005]. Thus,

[3] which is the same overall sample as in the study on efficiency in low-level haptic collaboration (Section 5.2.2). As dominance distributions are of no relevance in individual task execution, the "alone trials" are not considered here.

SRM explicitly models interdependence between two partners. As the method is not derived by the author, it is stated here for the sake of completeness, but is only summarized in brevity for the dominance analysis conducted here:

The amount to which partner 1 dominates partner 2 on average per trial and vice versa can be expressed as follows for a given condition:

$$\bar{PD}_{12,j} = \mu + \beta_1 + \gamma_2 + \delta_{12} + \epsilon_{12,j} \tag{6.2}$$

$$\bar{PD}_{21,j} = \mu + \beta_2 + \gamma_1 + \delta_{21} + \epsilon_{21,j}. \tag{6.3}$$

The parameter μ reflects a fixed effect, namely the mean individual physical dominance measure in a given group. This parameter is of no relevance as the SRM investigates variances. In the following, the first equation referring to partner 1 is described. Partner 2 can be analyzed correspondingly. The first random effect is β_1 which presents the actor effect, i.e. the *general tendency of partner* 1 *to dominate others*, across the k sub-trials and the different partners in the group. The random effect γ_2 describes the *general tendency of partner* 2 *to be dominated by others* across the k sub-trials and the different partners in the group. The third random effect is δ_{12} reflecting the *unique dominance constellation within a specific dyad*, here partner 1 and partner 2. The last component $\epsilon_{12,j}$ is the variance in the dominance measure in a given sub-trial j, which cannot be explained by the other components (*error term*). In the given data set there are three sub-trials and three different partners. It is important that the SRM is not directly interested in the size of the effect of this components as there is no causal effect due to specific predictors involved here, as it would be in ordinary regression approaches. Instead, the variance in these effects is the focus of the model. To give an example, the actor variance can be interpreted as an "estimate of the overall amount of variation in dyadic scores that is potentially explainable by characteristics of the individuals who generated them´´ [Kenny et al., 2006]. Thus, a large variance in the actor effect actually means that changes in the dominance measure are due to characteristics of the actor in contrast to interactive behavior towards the partner.

The goal of the social relations model is to examine the variance of the three random effects (σ_β, σ_γ, σ_δ). Hence, the variance found in all dominance measures in our dataset can be partitioned into the three above-explained sources, assuming an additive, linear relationship. Furthermore, the SRM distinguishes two types of reciprocity:
a) *Actor-partner reciprocity* or generalized reciprocity (covariance of β_1 and γ_1 has no meaning when analyzing dominance. This is due to the complementarity of dominance ($\bar{PD}_{12} = (1 - \bar{PD}_{21})$, compare Section 4.3.3: Negative generalized reciprocity ($\sigma_{\beta,\gamma}$) implies that persons who dominate others are not dominated by others. Thus, the parameters β_1 and γ_1 correlate with $r = -1$ by definition.
b) *Dyadic-reciprocity* (covariance of δ_{12} and δ_{21}: $\sigma_{\delta,\delta'}$) reflects the unique association between the dominance value of partner 1 and partner 2. This reciprocity provides information on the consistency of the dominance differences in the behavior of two partners across the three subtrials.

The analysis of the social relations model is conducted using the whole round robin dataset. The five variance/covariance parameters of the model are identified with the SOREMO program [Kenny, 1994]. All inference statistical results in the next section will be reported on a significance level of 5%.

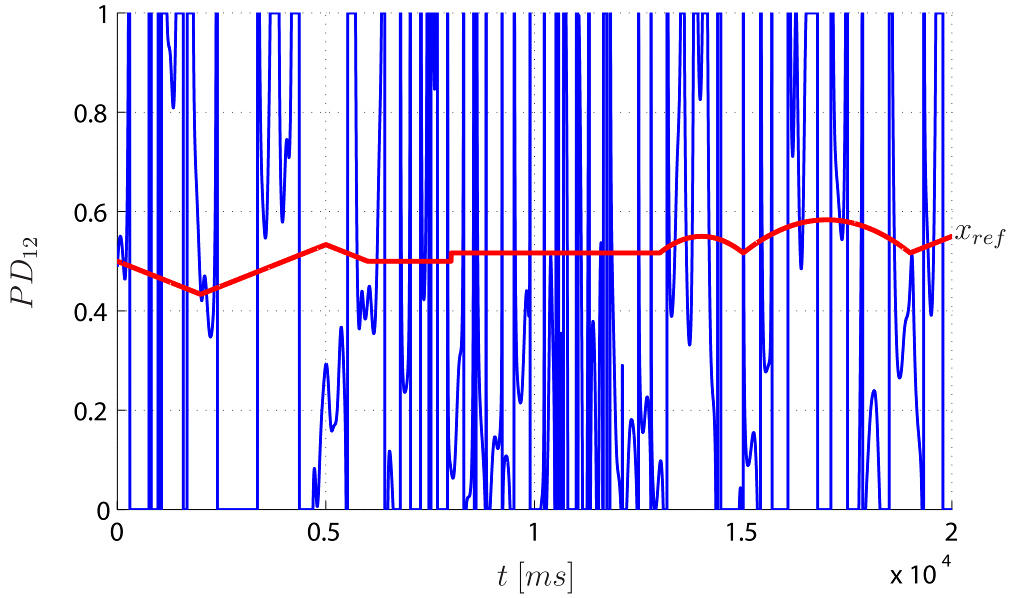


Figure 6.3: Exemplary dominance behavior of an individual participant ($D_{12,i}$) over time, condition with mutual haptic feedback (*VH*). The reference track is plotted independently of the scaling on the y-axis.

6.3.3 Results

In the following, the effect of mutual haptic feedback on physical dominance, the relationship between performance and physical dominance as well as the consistency of physical dominance behavior across several partners are analyzed taking into account the overall (mean) behavior per trial. This is in line with the state of the art in robotic implementation of dominance parameters, which are all time-invariant. Nonetheless, in Figure 6.3 an example of an individual physical dominance behavior is shown. The frequency of switching between dominant and non-dominant behavior is high, compared to the frequency of external forces, which are necessary to complete the task. These external forces necessary for task completion can be inferred from the reference track depicted in the same plot. It is concluded that the high frequency in the physical dominance measure is due to the fact that in our experiment the object has a low inertia and no damping is implemented which may lead to a higher frequency of overshoot than expected otherwise. As the following analyses focus on mean dominance behavior, the analysis of parameters causing dominance switches between partners is left for later studies.

RQ1 - Physical Dominance Distribution

The mean of the dominance difference ($\bar{PD}_{diff}$) in the two conditions with and without mutual haptic feedback of the partner is shown in Figure 6.4. In the vision-only condition the average difference was 17.29 percent points on the dominance scale (ranging from zero to 1) and in the vision-haptic condition 14.17 percent points . For the individual dominance it is observed that with a probability of 95% $\bar{PD}_{12}$ will not be higher than 0.6 (consequently not lower than 0.4 due to the complementarity of the measure) in the given task, independent of the feedback condition. A one-tailed t-test for each condition was conducted, to show that the dominance difference

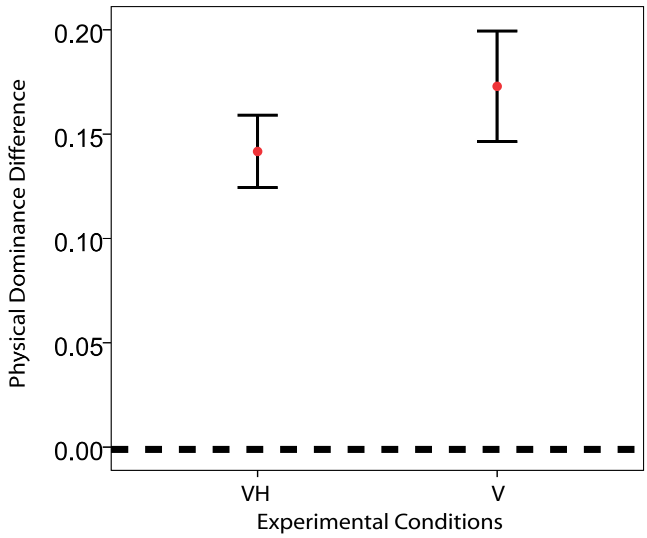


Figure 6.4: Comparison of dominance difference ($\bar{PD}_{diff}$) in the two conditions (*V* and *VH*); mean and standard errors. The difference between feedback conditions is small. In both cases a dominance difference can be found (values unequal to zero).

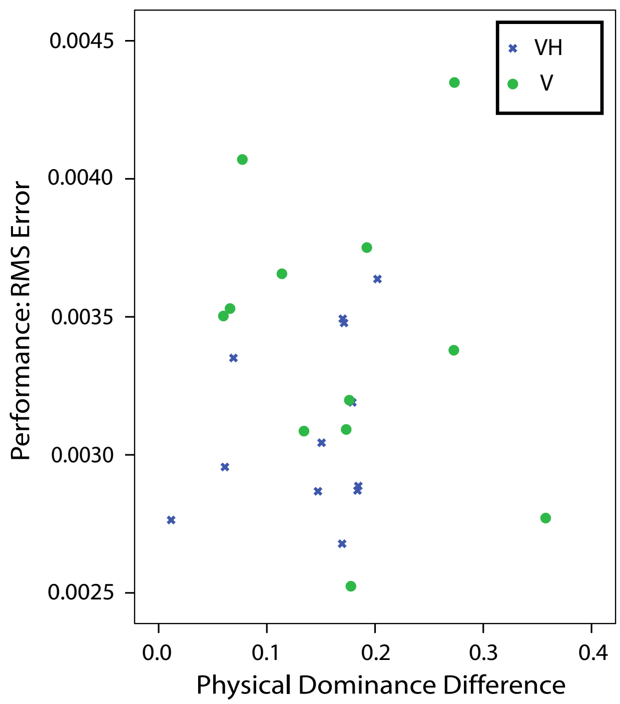


Figure 6.5: Correlation between the performance RMS and the physical dominance difference between partners ($\bar{PD}_{diff}$) separately for the two feedback condition with (*VH*) and without (*V*) mutual haptic feedback. As an inference statistic test on the significance of a correlation requires independent data, only values of twelve independent dyads are plotted. This limited sample does not allow to identify a clear pattern of the relationship between the two measures.

values differ from zero on the population level (V: $t_{11} = 6.517, p < 0.001, r = 0.891$; VH: $t_{11} = 8.149, p < 0.001, r = 0.926$). This means that on average participants worked with some dominance difference.

A paired t-test comparing the *V* condition (mean: 0.1729; standard deviation: 0.0919) and the vision-haptic condition (mean: 0.1417; standard deviation: 0.0602) reveals no significant difference between the two means of the dominance difference ($\bar{PD}_{diff}$): $t_{11} = -0.913; p = 0.381$. Hence, in the given experiment the feedback condition does not influence the mean dominance difference.

RQ2 - Physical Dominance and Performance

The relation between the empirically found mean physical dominance difference ($\bar{PD}_{diff}$) and task performance (RMS) is investigated separately for the two feedback conditions. Figure 6.5 depicts the correlations between dominance and performance. Descriptively no clear pattern can be found. The lack of correlation is strengthened by inference statistic tests using the Pearson correlation coefficient (*VH*: $r = 0.298, p = 0.347$; *V*: $r = -0.217, p = 0.499$): Neither of the two conditions show a significant correlation between $\bar{PD}_{diff}$ and RMS.

RQ3 - Consistency of Physical Dominance across Partners

The here reported results are based on the social relations model (see Section 6.3.2). The results from the SRM-analysis on variances in the mean *individual* dominance level ($\bar{D}_{12}$, $\bar{D}_{21}$) are reported in Table 6.1. The variance of the actor and partner effects (σ_β, σ_γ) are significantly different from zero in both conditions. The average individual dominance behavior, which is consistent across partners, explains 49.0% of the overall variance in the dominance measure in the *V* condition and 64.3% in the *VH* condition. The variances of actor and partner effects are considered together because they both relate to person-dependent behavior, which is not influenced by the interaction itself. The third variance component, the relationship σ_δ, determines the dyad-specific behavior: 32.8% in *V* and 24.7% in *VH*. However, the variation in this effect is not significant in the former condition and, thus, has to be interpreted with care. The higher amount of variance in actor and partner effects compared to the relationship effect implies that the average dominance behavior per interaction is rather person-dependent than due to the interaction with a specific partner.

The actor-partner reciprocity $\sigma_{\beta,\gamma}$ is -1.000 in both conditions, which is basically due to the dominance complementarity. The dyadic reciprocity $\sigma_{\delta,\delta'}$ states that the average dominance behavior between partners in the three sub-trials varies in both conditions (*V*: $\sigma_{\delta,\delta'} = -0.375$; *VH*: $\sigma_{\delta,\delta'} = -0.523$). Otherwise, a correlation of -1.000 would have been found here as well. However, due to the higher correlation in *VH*, it can be concluded that with haptic feedback of the partner the mean dominance behavior is more stable across time.

6.3.4 Discussion

In this section the focus has been on physical dominance, which takes into account control of the jointly manipulated object via forces and does not correspond to shared decision processes.

Table 6.1: Model estimates for *relative* variance partitioning (expressed in percentages) for actor, partner and relationship effects and the error term. If the amount of explained variance in $\bar{PD}_{12}$ is significantly different from zero, can be inferred from the p-values given below; significance on a 0.05 level is marked with *.

Condition		Actor σ_β	Partner σ_γ	Relationship σ_δ	Error
V	estimates	0.225	0.265	0.328	0.183
	p	0.038*	0.041*	0.051	
VH	estimates	0.353	0.290	0.247	0.110
	p	0.011*	0.022*	0.037*	

Thus, the experiment and its results address low-level haptic collaboration.

With 95% probability, no average dominance values outside the 0.4 to 0.6 interval are found in the given task, for both feedback conditions. Additionally, it is shown that humans work with some mean dominance difference in contrast to equally shared control (0.5) throughout the task. This is in line with the results found by Khademian and Hashtrudi-Zaad [2007a,b]. The results in this subchapter suggest that the humans collaborate with individually different action plans within the shared action plan of the dyad.

The current dominance analysis is based on mean values per interaction sequence, which corresponds to the state of the art in human-robot interaction, where time-invariant parameters for dominance distributions are implemented. For such time invariant dominance parameters, the results found in human-human collaboration in the current study imply, that passive following or absolute dominant position replay does not represent human-like behavior. Considering, however, time-varying dominance parameters, a sequential change between these roles may represent human-like behavior as suggested by the descriptive analysis. This subject needs to be addressed in future studies.

In line with the results presented by Rahman et al. [2002a] and Oguz et al. [2010], no evidence for a large effect of mean dominance distribution on performance is found. In Khademian and Hashtrudi-Zaad [2007a] it is reported that performance is higher with unequal physical dominance compared to absolute leadership. These results are, however, not directly comparable as they are based on a training scenario. Still, the relationship between dominance and performance may have been found because the values chosen to the dominance parameter in this study included non-human-like values. It is possible that physical dominance does not affect performance as long as the parameter values stay within an interval resembling human-human behavior. Non-human-like behavior could generally decrease task performance. This line of argumentation is strengthened by Oguz et al. [2010], who report that even though the dominance-adaptive assistance function did not increase results compared to the control conditions it led to higher rated human-likeness. Future work should address time-varying performance and dominance measures. This may allow finding a relation between those two measures.

The presented analysis allows statements on the consistency of average dominance behavior with a social relations model analysis: A high amount of the variability in average individual dominance behavior is consistent across partners (*V*: 49.0%, *VH*: 64.3%) and therefore considered as related to a character trait of domineeringness. Hence, a robotic partner can also represent a relatively consistent dominance behavior tendency, i.e. take over a certain dominance role (rather dominant or rather non-dominant). However, it is shown that 32.8% of the variance in mean individual dominance behavior in the *V* condition and 24.7% in the condition with mutual haptic feedback can be explained by interaction between specific partners. This is the amount the robot has to adapt to the human partner in order to create a intuitive feeling of interaction. So far, the adaptability of dominance behavior is based on mean values per interaction. However, the tendency already suggests that control architectures for robotic partners should address these two dominance components (the personal and the interactive component) separately. The fact that the dyadic reciprocity correlation has only small to medium size indicates that the mean dominance difference between partners varies between sub trials. In the haptic feedback condition the dyadic reciprocity is higher, leading to the conclusion that haptic feedback of the partner provides more stability (and hence predictability of the average human dominance behavior across time. This is in line with the results about the individual effort distribution between partners reported in Section 5.2, which is more fair when mutual haptic feedback is provided). Therefore, the findings of the consistency analysis support the recommendation to provide mutual haptic feedback for human robot haptic collaboration tasks, as modeling of the human partner should be simplified this way.

The analysis presented is based on an abstract experiment; especially, as the task involved only one-dimensional movements. Future work should investigate the distribution of physical dominance in multi-dimensional environments and different task. It is of interest, how the physical dominance in one dimension is related to the dominance in another dimensions (compare Wojtara et al. [2008, 2009] for different responsibilities on dimensions of workspace in human-robot collaboration). Furthermore, it was shown descriptively that the physical dominance behavior changes with high frequency between partners. In the current experiment this could be explained with the small inertia of the object or the lack of damping which may lead to a higher frequency of overshoots. As it seems still reasonable to assume that some variance in individual dominance behavior over time is shown even with other characteristics of the manipulated object, it is suggested that dominance should be considered as time-varying parameter in robotic architectures. As a first step to define guidelines for the change of values in this parameter over time, further analysis of human-human collaborative data is required.

6.4 Cognitive Dominance in Shared Decision Making (High-Level Collaboration)

In the previous subchapter on physical dominance, it was shown that averaged across an interaction sequence, one partner within the collaborating dyad is significantly more dominant than the other. Thus, there is evidence that the two individual action plans differ within the shared action plan when a given shared trajectory is jointly followed. Roles can be distinguished: One partner is more dominant in object control, i.e. applies more force resulting in object movement than the other. Now, the question is raised if the role of the partner who carries more physical workload (along with the definition of physical dominance) is necessarily the one who dominates in carrying out the cognitive workload in shared kinesthetic tasks, i.e. takes decisions on the trajectory the object should follow. Thus, cognitive dominance is not based on the measured applied forces but rather on the relationship between individually planned and jointly executed trajectory. The

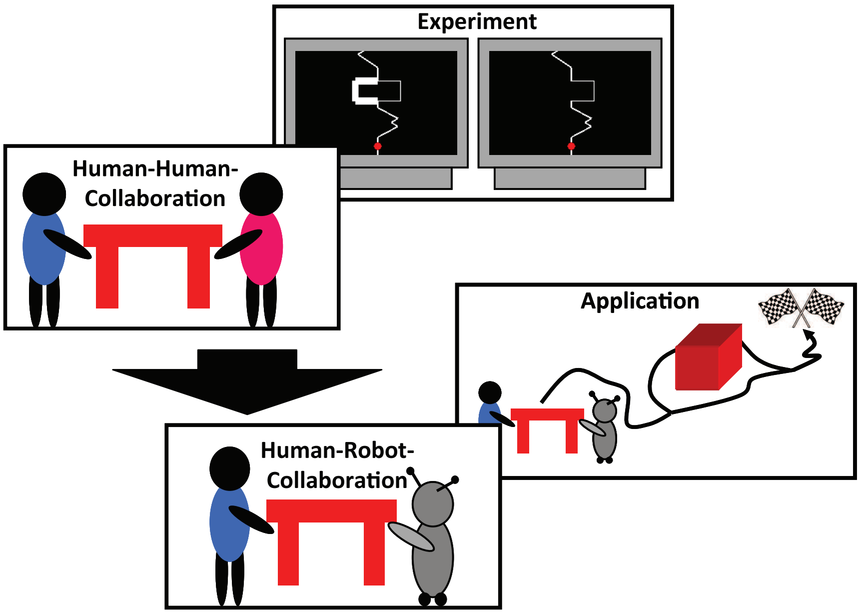


Figure 6.6: In line with the approach to learn from human dyads to enhance human-robot collaboration, this experiment investigates haptic collaboration of two human users with the shown setup including shared decision making.

subdivision of roles into a "workload-carrier" (executer) and a "decision maker" (conductor) has been formally suggested by Stefanov et al. [2009]. Note, however that so far this subdivision of dominance exists only on a theoretically basis and is investigated empirically for the first time in the following experiment.

In terms of shared action plans the question arises if the two levels which are proposed by the haptic collaboration framework find evidence, i.e. if the individual dominance within shared action plans are non-consistent for both levels. The two dominance measures serve as indicators in this matter.

Shared decision making (for a general overview see e.g. Castellan [1993]) is a cognitive task, which is of high importance for haptic collaboration: Whenever the trajectory of the jointly manipulated object or the interaction point between the two partners is not clearly defined by the task, the two partners have to negotiate and agree on an action plan, and thus, execute shared decision making. Examples of such not fully structured tasks are numerous: two partners (whether human or robot) want to carry an object and due to different environmental information they suggest different trajectories to do so. Or, a patient in a rehabilitation scenario has limitations in joint angles, which cannot be absolutely foreseen by a robotic therapist, who suggests an exercise and guides the patient. In these applications, shared action plans integrating these different individual plans have to be found. Intention negotiation has to take place. To our best knowledge, cognitive dominance in haptic shared decision making is not yet addressed experimentally in literature.

The experiment conducted in this subchapter involves a simplified scenario of shared object manipulation between human partners with binary shared decisions. In the chosen scenario, there is no a priori dominance differences as e.g. in the rehabilitation scenario. The experiment rather resembles a task between partners with an equal basis of background information and capabilities, which can be found e.g. in obstacle avoidance, compare Figure 6.6. In the present experiment, intention negotiation to derive shared action plans deals with the distribution of forces to move the object (physical dominance) and the trajectory where to move the object (cognitive dominance). In the previous chapter on intention negotiation (Section 5.3) it was shown that intention negotiation via the haptic channel can take place and increases performance. The decision situations, which are analyzed in the following, are designed to investigate individual roles instead of the dyadic performance outcome in shared decision making. Different decision situations are analyzed which can be separated clearly depending on the optimal cognitive dominance distributions between partners. Thus, it is of interest how performance-oriented the participants behave, i.e. if a participant dominates a decision situation when this leads to high performance and behaves non-dominant in other situations.

If we understand how physical and cognitive dominance roles are interrelated in human collaboration, it is possible to

- gain insights on how humans integrate individual action plans towards shared intentions in tasks requiring shared decision making
- understand if a separation of these two forms of dominance is feasible
- develop (based on the previous points) design guidelines for control architectures of robots, i.e. conclude on possible inferences a human may derive from robotic behavior and how the robot may predict which partner is going to take the decision beforehand, which simplifies online adaptation of the robot to the human partner

In order to investigate the general role of mutual haptic feedback between partners in joint object manipulation (which may not always be present in VR applications and may not fully be used for intention negotiation if the robot behaves non-human-like), an experimental control condition without mutual haptic feedback is studied additionally.

After introducing the research questions on cognitive dominance, information on the analyzed data set and the involved methods is given. Then, results in relation to the research questions are presented and discussed.

6.4.1 Research Questions

So far no experiments have addressed cognitive dominance in haptic collaboration. Due to this lack of knowledge, the following experimental analysis has an exploratory character. Within all research questions possible differences between the mutual haptic feedback condition and the vision feedback condition are addressed. In the presented study the following research questions (RQ) are investigated:

- **RQ1 - Cognitive Dominance Differences:** What are the cognitive dominance distributions across several decision situations? The analyzed decisions are designed in a way that allows best performance with *equal* cognitive dominance across all studied decision situations. The cognitive dominance difference in the behavior of human dyads is compared with the physical dominance difference as reported in the previous subchapter.
- **RQ2 - Cognitive Dominance and Performance:** Two new decision situations are introduced compared to the efficiency analysis in Section 5.3. In those new situations, only one

partner has the option to choose between two path alternatives. The other only has one path, and thus, should clearly dominate towards this option, resembling real life scenarios with clear restrictions. Now, the question is raised whether we can still find an advantage of mutual haptic feedback in these decisions of clear performance optimal cognitive dominance behavior, comparing it to a decision situation where both partners have two options with different preferences, i.e. cognitive dominance is not clearly instructed.

- **RQ3 - Physical and Cognitive Dominance:** How are physical and cognitive dominance related? Is there empirical evidence for two different dominance concepts as assumed so far in the conceptual framework? Can we predict which partner will cognitively dominate in a given decision situation based on knowledge of the physical dominance difference found in the partners' behavior before this situation?

6.4.2 Data Analysis

The experiment conducted to address high-level haptic collaboration is described in detail in Section 4.2. Here, more specific information for the present analysis of cognitive dominance are provided.

Participants

The analysis is based on the data of 29 independent dyads (58 participants; 5 male, 2 female and 22 mixed dyads; age mean: 25,78 (standard deviation = 4,87), which is the same sample used for the efficiency analysis for high-level haptic collaboration in Section 5.3). Due to the small strength necessary to collaborate in this task it is again assumed that the physical strength of participants does not interfere with the results.

Decision Situations

The three different decision situations, which are examined here, are depicted in Figure 6.7. Taking into account the overall goal of high task performance, these three decision types (*DT*) induce different cognitive dominance roles for the dyad:

- **P1-S** partner 1 has no choice between reference paths, thus if he/she wants to prevent errors (virtual object deviations from reference task) **P**artner **1** **S**hould be cognitively dominant. Thus, it is necessary to overrule partner 2 who will prefer another trajectory due to the preferences instructed to him by path thickness.

- **P1-SN** partner 1 is in a decision situation, preferring one out of two tracks due to path thickness. Partner 2 only has one option, a step in the opposite direction as the preferred path of partner 1. **P**artner **1** **S**hould **N**ot cognitively dominate here.

- **P1-C** both partners see two tracks, i.e. are in decision situations, but have opposite preferences due to path thickness: Here both partners can dominate, i.e. decide which track to choose. Who is cognitively dominant does not influence the possibilities in reaching high performance. From the perspective of partner 1: **P**artner **1** **C**an be cognitively dominant here.

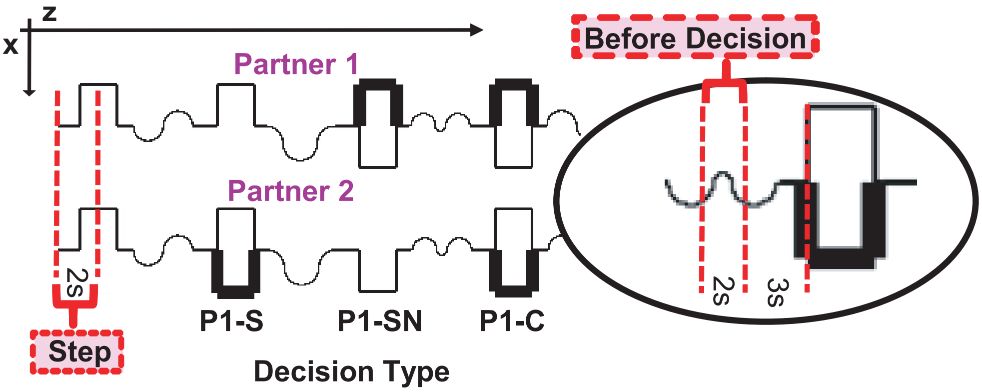


Figure 6.7: Example of paired reference tracks which "scroll down" the negative z-axis. In reality the paths are rotated by -90° see also Figure 6.6. Preference are instructed in decision situations as thicker path segments are easier to follow. The three analyzed decision types are named in relation to partner 1: *P1-S* Partner 1 should dominate here to show performance optimal behavior (stay on one of the tracks); *PS-SN* Partner 1 should not cognitively dominate to achieve good performance; *P1-C* Partner 1 can cognitively dominate as performance is independent of cognitive dominance behavior. The enlarged section depicts an interval of two seconds in which physical dominance is analyzed to compare the two different concepts in research question three.

Thus, the experiment is designed in a way that cognitive dominance behavior in decision situations will directly affect the dyadic performance in the decision situations *P1-S* and *PS-SN*. Each of the three analyzed decision types was repeated with interchanged sides within one trial to counterbalance a possible side bias (For *P1-S* and *P1-SN* four constellations of the two tracks had to be considered). This led to a total of eight analyzed decision situations. Each dyad performed one trial with and without mutual haptic feedback in randomized order. Each trial was executed with one of eight different tracks. These tracks varied with respect to the order of the presented decision situations. This way learning-effects were prevented through track repetition.

Measures

To analyze the first two research questions, the cognitive dominance measure introduced in Section 4.3.3 is used. However, in a first approach cognitive dominance is addressed with the simplified measure (defined in the following) by visual inspection:

$$\bar{CD}^b_{12} = \frac{\sum_{i=1}^{k} CD^b_{12,i}}{k} \tag{6.4}$$

where $\sum_{i=1}^{k} CD^b_{12,i}$ are the values of cognitive dominance of partner 1 over partner 2 based on the following coding schema: The instructed individually desired trajectory is similar to the executed trajectory as one:$CD^b_{12,i} = 1$; if the actual trajectory is more similar to the one desired by the partner: $CD^b_{12,i} = 0$. The analyzed decision situations (DS) were designed in a way that one partner had to dominate due to opposite preferences. Then, $k = \sum DS$ is the number of analyzed decision situations where cognitive dominance was possible (here eight). The same also holds for $C\bar{D}^b_{21}$. For further details see Section 4.3.3.

In decision situation *P1-C* (compare Figure 6.7) a partner was considered cognitively dominant when the cursor followed the path which was presented thicker to her/him. In the two remaining decision situations (*P1-S* and *P1-SN*) the partner, who saw only one path, was considered dominant if the cursor followed this one path and non-dominant if that was not the case.

In order to compare the cognitive dominance distribution with the physical one as part of research question one, the absolute difference measure of physical dominance is used ($P\bar{D}_{diff} = \left|P\bar{D}_{12} - P\bar{D}_{21}\right|$). For this comparison the mean physical dominance was calculated in a two second interval around a step, which was *not* part of a decision situation, compare Figure 6.7. In this way, the physical dominance values found in this interval should be comparable to those found in the previous chapter if there is no influence of the mere existence of decision situations in other parts of the interaction trial.

Comparable to the calculation with dyadic measure of physical dominance, the cognitive dominance difference in the partners' behavior in a given trial is expressed by the absolute difference between the individual measures ($C\bar{D}^b{}_{diff} = \left|C\bar{D}^b{}_{12} - C\bar{D}^b{}_{21}\right|$).

Performance is investigated with the root mean square error (RMS) based on the horizontal displacement between the desired position x_{ref} and the actual position x_o, introduced in Section 4.3.2. It is calculated in the two seconds interval around the actual point of decision (not depicted).

To answer research question three, both dominance concepts have to be measured. *Physical* dominance can be measured in track segments with and without decisions. However, *cognitive* dominance can only be studied in the presence of a decision situation. It is important to note, that cognitive dominance is not independent from physical effort: to dominate in a given decision situation it is necessary to apply forces in the direction of the chosen option to move the object in this direction or communicate to the partner to do so. Hence, cognitive dominance implies physical dominance in at least one time step here. To investigate if the partner who shows more cognitive dominant behavior is the one who applies more forces on the object throughout task execution, the physical dominance measure is used. To find out whether it is predictable if the physically more dominant partner will also take the next decision, physical dominance is measured before the decision itself, i.e. in the interval five to three seconds before the decision (compare Figure 6.7), where participants could see the upcoming decision situation. Here, the mean value for cognitive dominance is calculated: $P\bar{D}_{12}$. Due to the complementarity of individual values in both dominance measures it is possible to analyze only one partner to address research question three.

All inference statistical results in the next section are reported on a significance level of 5%.

6.4.3 Results

Before the differences of cognitive dominance within dyads are addressed, it is tested if the distribution of *physical dominance* in human behavior found in the previous study can be replicated here. The physical dominance in non-decision situations, i.e. the steps in the track, is investigated to clarify if the general existence of decision situations in the task affects physical dominance even in these task segments. As can be seen, in Figure 6.8 the results found here and in the previous subchapter look descriptively similar. This way the difference between

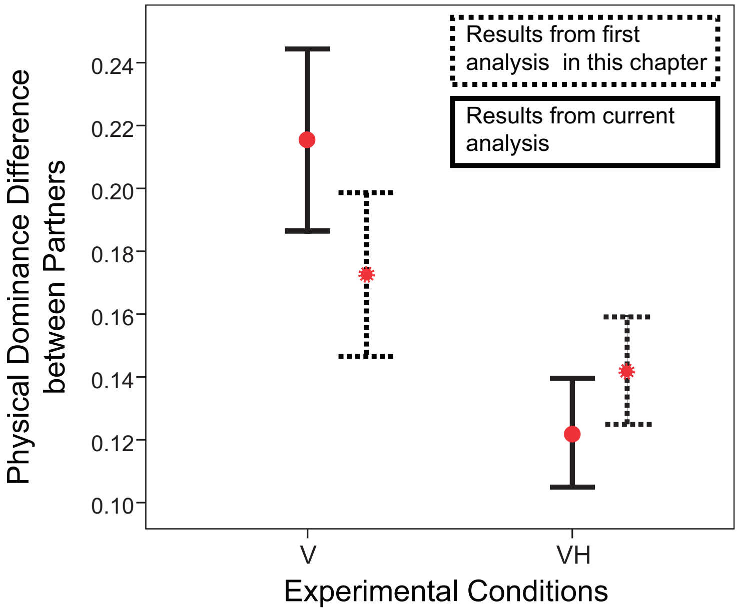


Figure 6.8: Values of mean physical dominance differences between partners (mean and one standard error) shown separately for the two feedback conditions (*V*: without mutual haptic feedback and *VH*: with mutual haptic feedback). The values are derived in a two second interval around a step not part of a decision situation, compare Figure 6.7. To contrast the current findings from the dominance differences reported in the previous subchapter, those values are repeated with dashed lines for the standard error.

the two feedback conditions becomes clearer in the current analysis: In contrast to the previously reported results on physical dominance differences between partners, the differences in the two feedback conditions reach significance: when mutual haptic feedback is provided the absolute dominance difference between partners in the analyzed interval is lower than without such feedback (paired sample t-test: $t_{28} = 3.059; p = 0.005; r = 0.501$. The correlation between the values of the two conditions, however, is not significant: $r = 0.211; p = 0.273$. In accordance with our previous results both feedback conditions lead to dominance distributions unequal to zero (meaning that the individual values differ significantly from 0.5 which would imply equal dominance; one sample t-test against zero: $V : t_{28} = 7.438; p < 0.001; r = 0.842$; *VH*: $t_{28} = 7.063; p < 0.001; r = 0.800$).

There are three possible reasons why in the current analysis the physical dominance difference is found to be significantly bigger without reciprocal haptic feedback: a) the sample size is higher compared to the previous analysis allowing more reliability of the results. A medium effect of haptic feedback is found here (compare effect size expressed in r), which may not have been detected in the earlier study with less statistical power. This argument is strengthened as the tendency to have more equal distributions between partners is shown descriptively in the previous study as well; b) the effect of feedback may be especially evident during the step response. Such an effect may then loose parts of its significance over the whole trial as it was analyzed in the previous experiment; c) the mere existence of decision situations throughout the interaction influences the dominance behavior. However, the difference between feedback conditions is still found. Only the size of the difference changed compared to the previous study.

The hypothesis found in the previous subchapter is further strengthened: with 95% confidence one partner will show more physical dominance than the other. In addition, this difference in pyhsical dominance is even stronger when no mutual haptic feedback between partners is provided.

RQ1 - Cognitive Dominance Differences

In order to investigate the *cognitive dominance* differences in human dyads, the absolute differences across ten different dominance situations is studied ($C\bar{D}^{b}{}_{12}$; all side combinations for each of the three types). The results on cognitive dominance differences between partners are descriptively similar to those of physical dominance (compare Figure 6.9). However, the difference in individual values for the vision condition is not significantly higher than that of the vision-haptic condition as found in the current analysis of physical dominance and, thus, the patterns resemble the dominance difference reported in the previous subchapter (dashed lines in Figure 6.8): paired sample t-test: $t_{28} = 1.394; p = 0.174; r = 0.254$; the Pearson correlation between two conditions is not significant: $r = 0.132; p = 0.495$). Again, both feedback conditions lead to significantly unequal mean dominance distributions between partners (one sample t-test against zero: *V*: $t_{28} = 14.520; p < 0.001; r = 0.940$; *VH*: $t_{28} = 13.020; p < 0.001; r = 0.926$). Thus, research question one can be answered by stating that the cognitive dominance difference between partners shows the same pattern as the physical dominance difference, i.e. one partner is significantly more dominant. This implies that one partner takes more decisions than the other, independent of the provided feedback. This is true, even though the chances to cognitively dominate are equally distributed between partners within the ten decisions.

RQ2 - Cognitive Dominance and Performance

In haptic human-robot collaboration it is of general interest to find performance-optimal behavior between partners. Research question two addresses this topic by analyzing the relation between the three decision types and the resulting performance. Performance (RMS error) difference between the two feedback conditions (*V* and *VH*) and the three decision types (*P1-S*, *P1-SN* and *P1-C*) is depicted in Figure 6.10. A 2*3 repeated measurement ANOVA reveals that mutual haptic feedback does not influence the performance ($F_{1,28} = 0.200; p = 0.658$). Thus, the performance benefits of mutual haptic feedback found in the efficiency analysis in Section 5.3, cannot be generalized to the current study, where instructed tracks are more restrictive and thus unfavorable dominance behavior can result in higher errors.

However, a significant effect of the decision type factor ($F_{2,56} = 15.691; p < 0.001; \eta_p^2 = 0.359$) was found. Bonferroni adjusted pairwise comparisons for the decision type factor showed, that there was no difference in performance whether partner 1 or 2 had to dominate (*P1-S*, *P1-SN*), but a significant difference to situations where both of them could dominate (*P1-C*, compare Table 6.2). This is in accordance with the instructed preferences and the task definition: In decision types *P1-S* and *P1-SN* one partner was assigned to show cognitive dominance by experimental design. If the corresponding partner does not dominate, i.e. makes the decision, this leads to an increased error as the dyad is then following a track, which is only instructed

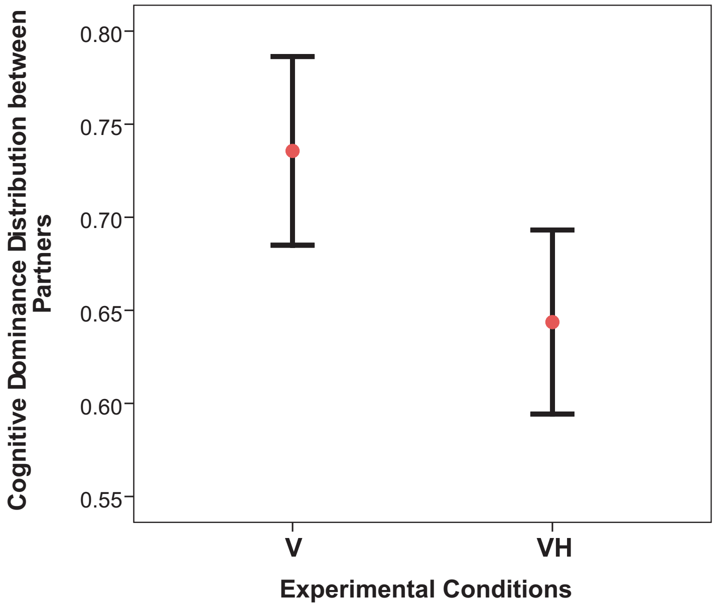


Figure 6.9: Values of mean cognitive dominance differences across decision situations (mean and one standard error) shown separately for the two feedback conditions (*V*: without mutual haptic feedback and *VH*: with mutual haptic feedback). The partner whose intended trajectory resembles the actual object trajectory is considered cognitively dominant.

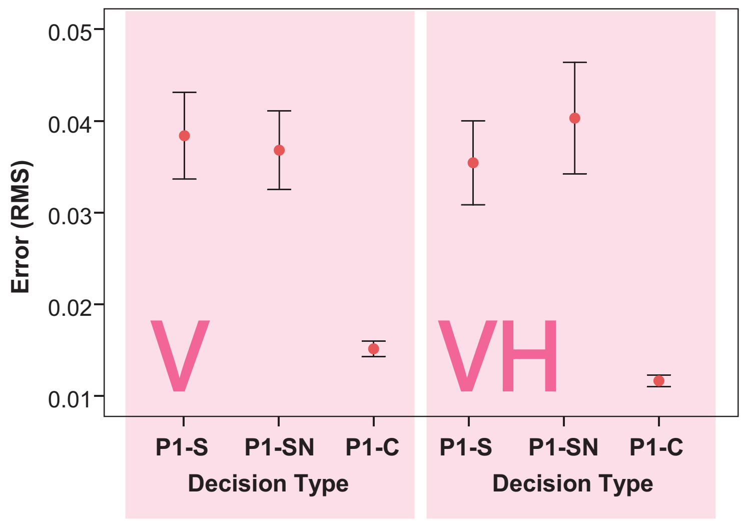


Figure 6.10: Mean performance values within in 2 seconds interval around decision situation (measured as RMS error, mean and one standard error) shown separately for the two feedback conditions (*V*: without mutual haptic feedback and *VH*: with mutual haptic feedback) and the three different decision types, instructing different performance-optimal cognitive dominance behavior for partner 1 and 2 correspondingly (*P1-S*: partner 1 should dominate; *P1-SN*: partner 1 should not dominate; *P1-C*: partner 1 can dominate)

.

Table 6.2: This table reports the p-values of Bonferroni adjusted pairwise comparison for the effect of the decision type factor on performance. Significant values on a 5% level are marked with *

Factor level	*P1-S*	*P1-SN*	*P1-C*
P1-S	-	1.000	< 0.001*
P1-SN	1.000	-	1.000
P1-C	< 0.001*	< 0.001*	-

to one partner. This problem cannot occur in decision type *P1-C*. Thus, performance analysis suggests that not all participants dominate or are non-dominant when they should. This implies that participants did not want to collaborate or were not able to do so successfully in all decision situations. As participants were instructed to collaborate and were told to be paid (for their participation in the experiment) based on the joint task performance, the results are interpreted towards the latter argument. One reason, why intention negotiation was not always successful could lie in the physical dominance executed by the partner. It may be challenging to the physically less dominant person to communicate his/her intentions in decision situations to a partner who is controlling the object movement most of the task. The relation between the two dominance concepts will therefore be examined in more detail in the next section.

RQ3 - Physical and Cognitive Dominance

In this paragraph the relation between physical and cognitive dominance is analyzed. Keeping in mind the overall goal to *predict* the cognitive dominance, the physical dominance is calculated as a mean value in a 2s interval five to three seconds *before* the decision ($P\bar{D}_{12}$). Cognitive dominance (CD^b_{12}) is coded binary (0 = non-dominant, 1 = dominant) in a given decision situation and thus, a dichotomous variable. As a first approach, a conditional density plot is examined, depicted in Figure 6.11. It describes how the conditional distribution of cognitive dominance values change over physical dominance values. Only partner 1 is analyzed in the following. Due to the complementarity of the measures the values of partner 2 are implied. The plot suggests a relation between the two dominance concepts: higher $P\bar{D}_{12}$ values lead to a higher probability for $CD^b_{12} = 1$ (lighter area in plot) and vice versa.

Motivated by these descriptive results the goal is now to model the individual cognitive dominance behavior. There are several predictors, which could influence CD^b_{12}, above all $P\bar{D}_{12}$ and the factor decision type (*DT*, with three levels). A regression approach is chosen to analyze the influence of these variables on CD^b_{12}. Due to the fact that cognitive dominance is coded binary in the current analysis, this cannot be done with ordinary least square (OLS) regression, which assumes interval scaled outcome variables Cohen et al. [2002]. Instead a generalized linear model, in particular a logistic regression is chosen, which predicts the probability (binomial distribution) for being either one of the cases. Thus, the probability $P(Y)$ for a variable Y to be 1 implies that $(1 - P(Y)) = 0$. Herein, Y is defined to be $= CD^b_{12}$. The relation between these probabilities

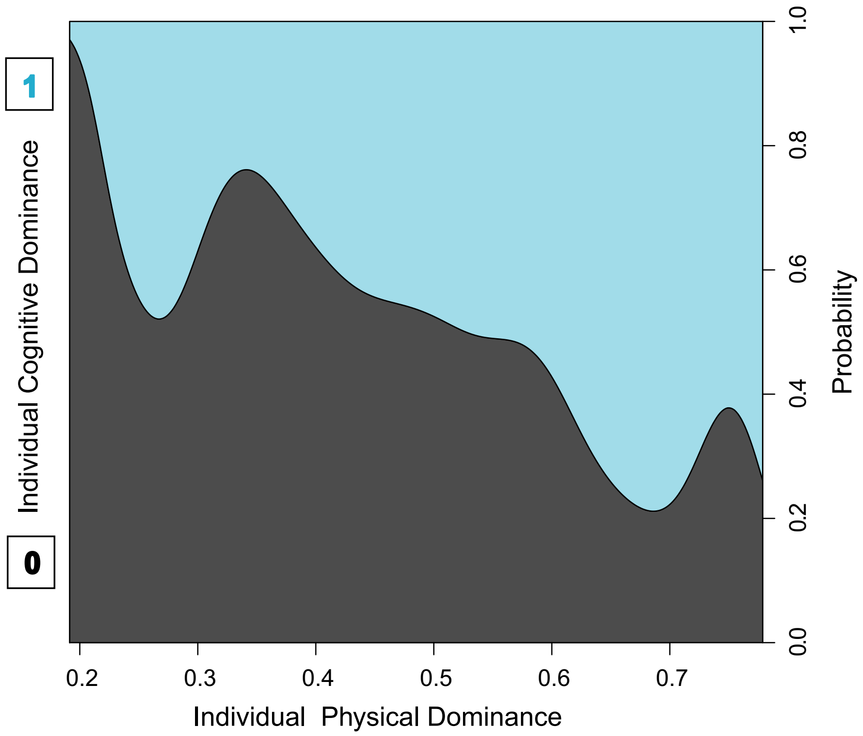


Figure 6.11: Conditional density plot describing the conditional distribution in cognitive behavior ($CD^b_{12} \in [0, 1]$) depending on physical dominance values (PD_{12})

and a predictor X can than be described in a non-linear, s-shaped way:

$$logit = ln(\frac{P(Y = 1)}{1 - P(Y = 1)}) = B_0 + B_1 X \tag{6.5}$$

where $B_0 + B_1 X$ (X is a predictor and B_0 and B_1 regression coefficients) is the linear formula for a single predictor known from OLS regression.

Another challenge when applying a regression model to the cognitive dominance data is the repeated measurement design, given by the fact that participants provided data for all levels of the feedback and the decision situation factor. The possible dependence in data for the different levels breaks the independent error assumption of regression models. The solution used here is the explicit modeling of a random dyad factor which addresses the variance in cognitive dominance (Y) due to a dyad specific offset (thus, a varying intercept model is applied). This means that the above described logit model has to be extended by a random effect (b_r), which is assumed to be normally distributed with mean zero and variance σ_b^2. Further considering the fact that the number of possible predictors (X) is not yet specified, a general matrix multiplication is used to describe the general model. Thus, the generalised linear mixed model for binary responses assumes a Bernoulli distribution for each response Y_{dk}, with $d = 1, \ldots, l$, (as index for dyads) and $k = 1, \ldots, n$ (as index for a measurement within a dyad), given the subject specific random effect b_r. The conditional mean of Y_{dk} depends on the fixed ($\mathbf{X}_{dk}$) and random (b_r) effects via the following linear predictor:

$$\eta_{dk} = \mathbf{X}_{dk}^{\top} \mathbf{B} + b_r \ ,$$

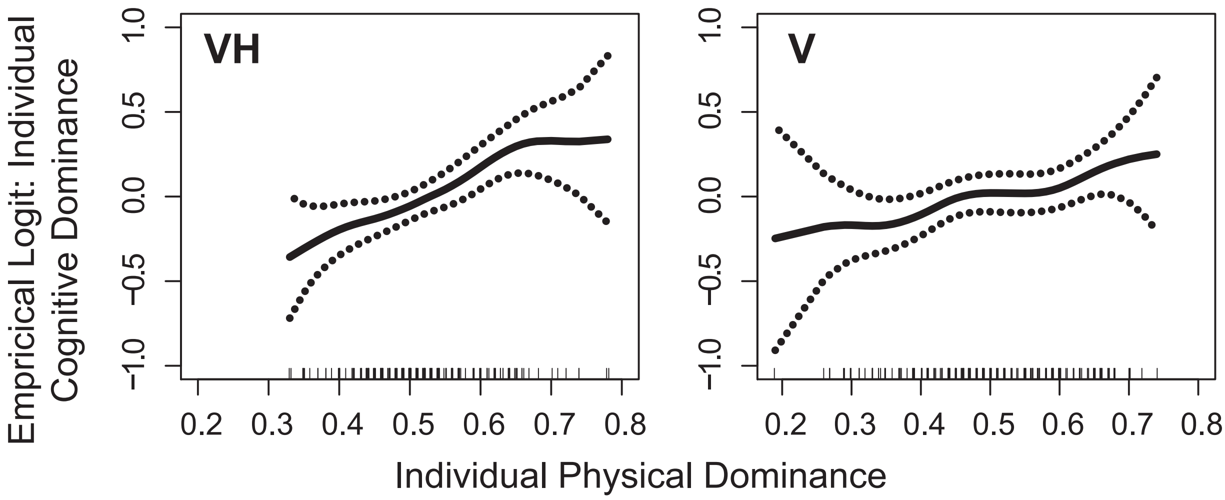


Figure 6.12: Empirical logits of individual cognitive dominance behavior with physical dominance as only predictor. This is done across all decision types, separately for the two feedback conditions (*V* and *VH*). The dotted lines show the standard errors.

for all $d = 1, \ldots, l$ and $k = 1, \ldots, n_d$ with

$$\ln \left\{ \frac{P(Y_{dk} = 1|b_r)}{P(Y_{dk} = 0|b_r)} \right\} = \eta_{dk} \, .$$

The model can be extended to include also random influences of certain covariates, but in our case a model with randomly varying intercept is enough. For further details on generalized linear mixed models the reader may refer to Fitzmaurice et al. [2004] and Gelman and Hill [2008].

When modeling the binary response CD^b_{12}, a numerical covariate of interest is physical dominance $\bar{PD}_{12}$ before the decision situation, and a number of possible categorical covariates (factors) such as *decision type* (*DT*) and *feedback* (*FB*). Furthermore, the possibility exists that participants have a *preference for one side* of motion (pushing or pulling the object), which then should result in a trade-off in cognitive dominance depending on the instructed side of decision preference. However, the more predictors involved in a model the lower its statistical power. Therefore, the following descriptive analyses have the goal to gain information on which predictors should be included.

First, the effect of physical dominance is examined on the empirical logit of the cognitive dominance values, see Figure 6.12. As can be seen, a (nearly) linear relationship between the two dominance variables exists (for more information on empirical logits compare e.g. Abraham [1999]). Descriptively comparing the slopes, the relationship between the predictor ($\bar{PD}_{12}$) and the dependent variable (CD^b_{12}) seems stronger when mutual haptic feedback is provided (compare slopes). Therefore, a model should be fitted with an interaction between the predictors physical dominance and type of feedback to address these differences.

In Table 6.3 a possible side bias is investigated by comparing the relative frequencies to move to the left or the right in a decision situation in relation to cognitive dominance. The bias towards the right side in dominant behavior is considered small enough to neglect it in this early stage of modeling the relationship between the two dominance concepts.

Depending on the decision types (*P1-S*, *P1-SN*, *P1-C*), which instruct certain dominance be-

Table 6.3: Proportions of cognitive dominance behavior separately for the two sides of the instructed preferences in the decision situation.

	left side	right side
$CD^b_{12} = 0$	0.474	0.529
$CD^b_{12} = 1$	0.526	0.471

Table 6.4: Proportions of cognitive dominance behavior shown separately for the behavior instructed by the decision type (*DT*) via different decision options/preferences for the two partners.

	DT: *P1-S*	*DT*: *P1-SN*	*DT*: *P1-C*
$CD^b_{12} = 0$	0.696	0.304	0.500
$CD^b_{12} = 1$	0.304	0.696	0.500

havior, differences between the proportions of cognitive dominance are more distinct (compare Table 6.4): in nearly 70% of the observed cases partner 1 behaves in the optimal way when he/she should dominate (condition *P1-S*) or should not do so (condition *P1-SN*) (compare also the discussion of results related to the previous research question). The relative frequencies for the two possible outcomes in cognitive dominance are of the same size when both partners can dominate (*P1-C*). Taking into account all three levels and their descriptive effect on the cognitive dominance, it is decided to include this factor in the model. Eventhough the introduction of further predictors and interactions between predictors may be theoretically possible. It is decided against this to ensure the statistical power of the model and to act in line with Ockham's razor [EncyclopediaBritannica, 2010]. However, there is awareness that future work may consider different predictors in this context.

Based on these considerations the generalized linear mixed model which will be fitted to the experimental data can be described as:

$$ln \left\{ \frac{P(CD^b_{12,dk} = 1|b_r)}{P(CD^b_{12,dk} = 0|b_r)} \right\} = B_0 + B_1 \bar{PD}_{12,k} + B_2 \mathit{FB} + B_3 \bar{PD}_{12} \mathit{FB} + B_4 \mathit{DT} \tag{6.6}$$

where *FB* (feedback factor) and *DT* (decision type) are both categorical variables which are dummy coded here. The index k represents the different decicision situations.

In Table 6.5 the estimated model parameters are given, together with the standard error and the p-value to address the significance of the parameters. The analysis is designed such that the model predicts the probability of cognitive dominance, i.e. dominant behavior. The fact that the intercept does not reach significance suggests a sufficiently explained variance in the CD^b_{12} values by the fitted model. The reference category of the feedback factor (*FB*) is the condition without mutual haptic feedback (*V*). The positive sign of the physical dominance predictor ($\bar{PD}_{12}$) therefore implies that cognitive dominance increases if physical dominance was given by this person before the decision situation. This predictor reaches significance. In the feedback factor the vision condition (*V*) is chosen as reference category and the predictor thus informs

Table 6.5: Estimated parameters of the fixed effect coefficients in the model described in Equation 6.6 along with corresponding standard errors and p-values. For the categorical predictors the level of the factor is named towards which the reference category changes (reference categories: for feedback factor, *FB*: *V* and for decision type factor *DT*: *P1-S*). Significant effects on a 5% level are marked with *.

	Estimate	Std. Error	p
(Intercept):	-1.232	0.798	0.123
$\bar{PD}_{12}$:	4.305	1.551	0.006*
FB: *VH*:	-2.263	1.363	0.097
DT: *P1-C*:	-0.887	0.291	0.002*
DT: *P1-SN*:	-1.748	0.305	$<$0.001*
$\bar{PD}_{12}$ * *FB*: *VH*:	4.032	2.622	0.124

on the changes in cognitive dominance when haptic feedback is provided (*VH*). The interaction between physical dominance and the feedback factor does not reach significance. Instead, the main feedback effect is examined: The negative sign in the estimate of the feedback predictor states that with haptic feedback it is less likely for the partner to dominate compared to the vision condition. However, this predictor is not significant on a 5% level. In relation to the descriptive results given in Figure 6.12, an effect of this factor may be too small to be detected with the given sample size. The factor decision type has a larger effect on cognitive dominance as it reaches significance. The reference category here is decision situation *P1-S*, where cognitive dominance is instructed. Interpreting the sign of the estimate of the predictor for a decision situation of type *P1-C*, it is concluded that it is less likely to dominate in this situation compared to *P1-S*. For decision type *P1-SN*, the estimate is larger and again negative, stating that the probability to show cognitive dominance is even more decreased when partner 1 should not be dominant. These results are in line with the instructed behavior.

The random effect considers a different intercept for each of the 29 dyads. The estimated variance of these intercepts is rather small ($\hat{\sigma}_b^2 = 0.0948$). This shows that the dyads behave very similar. In Figure 6.13 the empirical quantiles of the estimated random intercepts are compared to the quantiles of a normal distribution. Since there is only little deviation from the straight line (representing normally distributed values), the assumption of a normally distributed random effect seems to hold. The differences in the intercepts between the dyads is, thus, modeled correctly but can be disregarded due to its size.

To investigate the fit of the model and to illustrate its predictive capabilities for the given scenario, Table 6.6 reports the expected (from the model) and empirically observed values of cognitive dominance. The fitted values are shown separately for the two feedback conditions (*V* and *VH*). Even though this factor did not reach significance as a predictor, descriptive differences in the relation between physical and cognitive dominance are found. For application in robotic research it is of interest to find out how well the model predicts under which feedback condition. As the instructed cognitive dominance is equally distributed between partners across the ten observed decision situations, the probability to show cognitive dominance is 0.5 without applying a model:

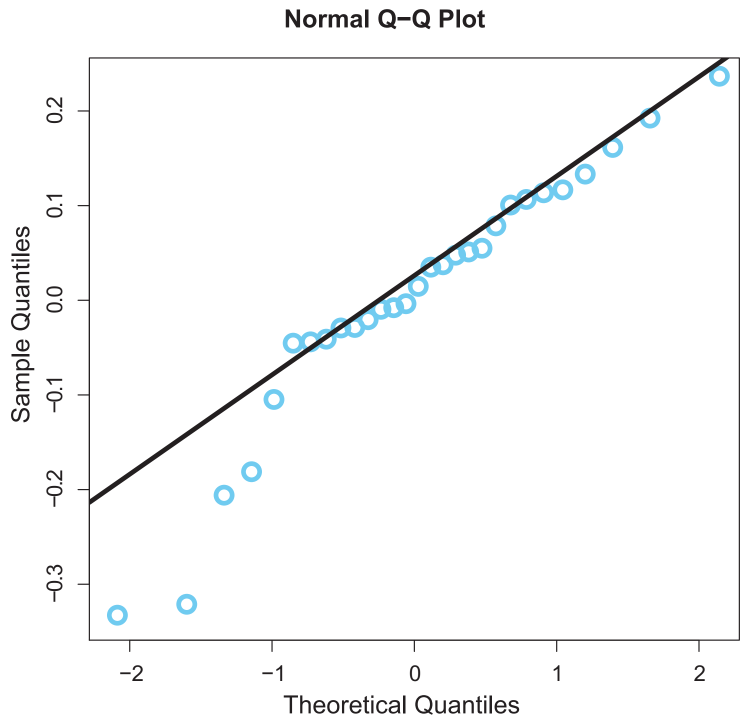


Figure 6.13: Normal qq-plots of estimated residuals (compare e.g. Field [2009] for more information on qq-plots)

$$CD_{12}^{b} = \begin{cases} 0 & \text{with } P = 0.5 \\ 1 & \text{with } P = 0.5 \end{cases} \tag{6.7}$$

The probability of predicting cognitive dominance behavior correctly is increased to over 70% when the model is applied in the haptic condition. Thus, knowing the individual constrains in decision situations (decision types) as well as the physical dominance measured before this situation gives valuable information about which partner will take the decision. When haptic feedback is not provided, the chance of a correct prediction of the cognitive dominant partner is around 65%. Predictability of the partner increases with mutual haptic feedback. However, the model does not describe the data well enough to make absolutely correct predictions (100%); a error probability of 27-29% is still high. Thus, the results show a relation between the two dominance concepts on the one hand, but also motivate research, which addresses physical and cognitive dominance separately.

6.4.4 Discussion

In this subchapter cognitive dominance in a shared decision task based on haptic collaboration was investigated in relation to physical dominance. First insights how individual action plans are integrated into a shared action plan could be gained.

The cognitive dominance difference is similar to the one reported in the previous analysis on physical dominance: in both dominance concepts it is found that participants preferred to work with unequal dominance, i.e. one partner is leading more than the other. The results reported here

Table 6.6: Comparison of a) cognitive dominance predicted by the above described model, and b) observed cognitive dominance. Percentages for correct and false prediction are given within the cells. The colored cells indicate the correct classification of dominance behavior.

	predicted CD^b_{12}	VH $CD^b_{12}=0$	$CD^b_{12}=1$	V $CD^b_{12}=0$	$CD^b_{12}=1$
observed CD^b_{12}	$CD^b_{12}=0$	0.724	0.276	0.640	0.3601
	$CD^b_{12}=1$	0.291	0.709	0.345	0.655

are in line with the finding of Rahman et al. [2002a] on physical dominance. In this subchapter, reporting mean values of preferred cognitive dominance in human dyad behavior could extend those results. This is the first time that cognitive dominance behavior of humans was explicitly studied.

The experiment reported here was designed in a way that led to high performance errors if participants did not dominate when they should or vice versa. An interpretation of the resulting performance is therefore highly dependent on the applied analysis. However, independent of the performance measures underlying this analysis, no difference depending on the provided feedback could be found. This is contradictory to the results reported in the efficiency analysis of intention negotiation in shared decision making in Section 5.3. The performance benefit in relation to mutual haptic feedback found there could not be strengthened in the current study. Even with mutual haptic feedback participants where not always able to show performance-optimal cognitive dominance behavior (only in 70% of the cases). One explanation for this findings may be found in the fact that different decision types where analzed in the two studies. Further, the different results may be due to the fact that decisions had to be made under time pressure (reference path scrolling down) and that a threshold for showing physical dominance to convince the partner towards one's own cognitive dominance exists. Further investigations in this direction will be part of future studies. The relationship between physical and cognitive dominance has been introduced only on a theoretical basis so far. Now,for the first time an experimental study was performed to test the predictability of cognitive dominance based on physical dominance shown *before* the decision situation. Next to physical dominance the model tested feedback and decision type as possible predictors and considered a dyadic level random effect. Only the physical dominance and the decision type influence cognitive dominance in the given data set. The probability to show cognitive dominance, i.e. lead in a shared decision, changes in accordance with the task requirements in the situation, i.e. if the reference paths instructed cognitive dominance. The physical dominance significantly determines the cognitive dominance in a subsequent decision situation. However, cognitive dominance can only be predicted with 70% accuracy based on the applied model, considering conditions with mutual haptic feedback. Thus, cognitive dominance is not fully explained by physical dominance even though a correlation exists. Therefore, it is recommended to measure those two concepts separately in future studies. Furthermore, the model evaluation shows a 5% difference of accuracy depending on the provided feedback. The current study should be interpreted as a frist attampt to model the realationship between the two dominance concepts. Results will clearly motivate the usage of more adavanced, time-dependent models in this context in future.

6.5 Conclusion

6.5.1 Summary

In this chapter dominance behavior between two humans in haptic collaboration was experimentally investigated. Herein, physical dominance, which measures how individual force inputs are combined when moving the object along a trajectory, and cognitive dominance, which measures which partner is dominant in decisions on where to move the object, i.e. which trajectory is followed, were considered separately. The two dominance analyses on human behavior enable an investigation of how the individual partners contribute to the shared actions within the haptic collaboration task.

Human-like **physical dominance** behavior is characterized by non-equal dominance values for the interacting partners in the analyzed tasks. i.e. one partner is more dominant than the other. For the first time, quantitative information on how humans combine their force inputs in a haptic collaboration task can be reported: the 95% confidence interval for the mean individual physical dominance behavior is 0.4 to 0.6, implying that *time-invariant* passive following and position replay do not resemble human-like behavior. No correlation between task performance and the executed physical dominance behavior was found. Analyzing the variance in mean individual physical dominance behavior across different partners and subtrials revealed that mutual haptic feedback leads to higher consistency in dominance behavior. For both feedback conditions, a higher amount of variance in the individual behavior can be explained by the partner compared to variance explained by dyad-specific interaction.

Similar results could be found for **cognitive dominance**: one partner shows significantly more dominance in decision situations than the other, independent of the provided feedback. In this task, the correlation between cognitive dominance and performance could not be directly addressed as it is partly determined by the experimental design. However, again no differences depending on the provided feedback could be found. To the author's best knowledge, the analysis reported here is the first approach to address the relation between physical and cognitive dominance, investigating whether the partner, who is physically dominant before the decision, also leads in the following shared decision situation. The applied model showed that cognitive dominance could be predicted correctly in 70% of the cases when the mean physical dominance value before the decision and the decision situation (including the individual environmental restrictions) was known and mutual haptic feedback was provided. Even though it is not clarified yet how relevant the results found are when executing other haptic collaboration tasks, quantitative information on human dominance behavior could be gained. Now that clear hypotheses on dominance behavior can be defined, the methods used in this analysis can easily be employed to investigate further tasks to increase knowledge on the integration of individual actions in haptic collaboration.

6.5.2 Future Work

The experiments conducted consisted of a simplified scenario of joint object manipulation involving only one degree of freedom movements. The abstraction of real life scenario enabled a focus on basic rules, which are harder to detect in more complex scenarios. Results suggest promising rules to describe human-like behavior in haptic collaboration and thus, how the shared actions are derived from individual inputs. As a next step the dominance measures should be applied in experiments of higher complexity to test the generalizability of these rules. The studies reported here provide substantial motivation to do so.

Further experiments should address physical dominance as a time-varying parameter. To the author's best knowledge no robotic architecture provides this feature yet. However, it could be implemented easily once the characteristic of the human behavior over time is known and there is experimental evidence that there is explainable variation from a constant value.

In the studies reported here, no correlation between the executed dominance behavior and performance was shown. It was suggested that this is the case because the dominance behavior was human-like. In Khademian and Hashtrudi-Zaad [2007a] it is reported that equal dominance distribution and clear leadership (non-human-like behavior) decrease performance. For the design of performance-optimal robotic partners further studies are necessary.

For a first approach on the relation between cognitive and physical dominance a simplified binary measure for cognitive dominance was used. To investigate this relation in more detail, future studies can additionally rely on the continuous cognitive dominance measure introduced in Section 4.3.3. Furthermore, it is suggested to shed further light on the relationship between the two types of dominance measures, as well as the relationship between them and performance by conducting analyses on the basis of questionnaire data investigating the similarity to human behavior.

6.5.3 Design Guidelines for Robotic Partners

Based on the above-summarized results on dominance, design guidelines for technical partners can be derived in line with the goal to develop robots, which allow for an intuitive collaboration.

For physical dominance values, a precise interval in which behavior can be considered human-like could be detected. Thus, time-invariant physical dominance values in robotic architectures should be within this interval for one-dimensional tasks. It is suggested to conduct follow-up studies for more complex scenarios. For variation within this interval two different sources could be found: consistent behavior, which is interpreted as due to a character trait of domineeringness and an interactive component, which changes with a specific partner. The percentages of explained variance of these two components allow a precise statement on the required changes in time-invariant physical dominance parameters of a technical partner for a specific human user. As the first component the consistent dominance behavior explains more than 64%, it can be concluded that only limited change in the physical dominance parameter is necessary as long as mutual haptic feedback is provided. This general advantage of mutual haptic feedback to stabilize the individual behavior, already reported in Section 5.2, finds further evidence here. Thus, it is generally recommended to provide mutual haptic feedback despite the technical challenges as it promises a higher predictability of the human partner and therefore, easier interpretation of the required actions from the robotic partner.

Architectures of technical partners should contain different modules for cognitive and physical dominance, as these concepts do not correlate high enough to consider them to be identical. Cognitive dominance can partly be predicted from physical dominance. Therefore, the design of a module related to physical dominance (e.g. α values, compare Evrard and Kheddar [2009]; Khademian and Hashtrudi-Zaad [2007a,b, 2009a,b]; Nudehi et al. [2005]; Oguz et al. [2010]) may influence the mental model of interacting humans with respect to upcoming decisions and related assumptions on restrictions in the partner's environment. Again, additional studies are required to provide further information on tasks of higher dimensions. Limiting the statements to one-dimensional haptic collaboration, the following recommendation for robotic partners can be given: It is advisable that a robotic partner reduces its physical dominance if he has information on an approaching decision situation, however, does not know the optimal option. This should indicate to the human user that the robot is not taking the decision and thus, a smooth shared action plan can be established by the human.

The proposed dominance measures and the experimental designs employed in this chapter enable further investigations of dominance. The developed dominance measures (Section 4.3.3) are seen as a promising tool when aiming understanding adaptation processes between collaborating partners in haptic tasks. Therefore, future work can relate to the presented analyses when investigating the structure of adaptation modules in robotic partners as proposed in the haptic collaboration framework (Chapter 2).

7 Overall Conclusion and Future Direction

7.1 Concluding Remarks

This dissertation has explored human dyad behavior in haptic collaboration tasks with the goal of identifying requirements for the design of robotic partners in order to enable intuitive collaboration in this context. This goal has been approached successfully by the following **contributions**:

- A **conceptual framework** for haptic collaboration has been presented. It summarizes requirements of models for partners in haptic collaboration. Guidelines for control-theoretic models are provided. One important aspect of the framework is the separation into two levels of haptic collaboration: The higher level is defined by intention negotiation between partners *where* to move, i.e. shared decision making. The lower level focuses on *how* to move, i.e. on strategies how to combine the two individual force outputs.

- A **discussion on characteristics of state-of-the-art experiments** in the research field has been given, stating an increased interest in interdisciplinary research of haptic collaboration. A need for further, systematic investigations on haptic collaboration has been identified.

- **Two new experimental designs** have been introduced with the corresponding setups in order to enable studies on haptic collaboration. The experiments have been conducted to address the two levels within the haptic collaboration framework iteratively. It is now possible to study shared decision making in haptic collaboration. In addition, **measures** in the context of haptic collaboration are presented based on a general description of force components of relevance in haptic collaboration. One efficiency and two dominance measures have been introduced.

- **Intention negotiation** was investigated via an efficiency analysis. For the first time it could be shown that intention negotiation is actually possible for humans via the haptic channel. Furthermore, the physical effort related to haptic collaboration has been investigated for the first time.

- **Shared actions** in haptic collaboration require the integration of two individual force outputs and an agreement on the jointly followed desired trajectory. How the individual intentions are combined towards a shared action has been addressed by an analysis of dominance distributions. Physical and cognitive dominance are distinguished referring to the lower and higher level of haptic collaboration. A correspondence between the two dominance types has been shown. The degree of adaptation in physical dominance behavior towards different partners has been quantified. Changes in cognitive dominance behavior depending on different shared decision situations has been investigated.

- **Design guidelines** for robotic partners in haptic collaboration have been inferred based on these experimental results. They state, for example, under which conditions mutual haptic feedback leads to performance- or effort-optimal collaboration, or the required changes in dominance across different human partners.

The work presented here provides the following **implications for future research** in haptic collaboration:

- The framework structures the research presented, but additionally serves as a tool when integrating existing research. It simplifies the planning on future studies in haptic collaboration by enabling a specification of the experimentally addressed concepts in a broader context. Future attempts in dynamic modeling of haptic collaboration partners find guidelines on required components and signal flows in the framework.
- The discussion on existing experiments in haptic collaboration provides tools and examples to conduct interdisciplinary research in future. The newly developed experiments and the introduced measures allow for analyses beyond those reported in this dissertation, and thus, provide a valuable contribution to the research field.
- The relevance of insights and design-guidelines experimentally derived in this thesis is already shown by ongoing control-theoretic modeling and evaluation experiments at the Institute of Automatic Control Engineering at Technische Universität München.

7.2 Outlook

The results reported here enabled the identification of significant behavior rules. These are derived in an abstract, one dimensional object manipulation task. Within this limited setup, the influence of factors such as mutual haptic feedback, a partner or the need to negotiate intentions could be shown. Guidelines on dominance behavior have been presented. Future work will have to investigate how generalizable the results are with respect to more complex scenarios in terms of the manipulated degrees of freedom, the task itself and object characteristics. The framework, the experimental methods and the measures introduced in this dissertation provide profound information on This thesis has focused on behavioral measures when describing the human behavior. These measures are of high relevance for quantitative statements required for the design of future robotic partners, and are in general more reliable than subjective measures, i.e. questionnaires. However, future work in haptic collaboration research should focus on an integration of these two measurements, e.g. identifying equivalents between both types to gain a more complete picture of the user experience in collaboration and simplify its measurement by focusing on the most significant. Questionnaire data on efficiency, presence, collaboration and dominance are available for all conducted experiments to be used in future analyses. Additionally, one particular challenging measure of interest is mental effort (compare e.g. [Wickens, 2004, Chapter 13]).

In future, the data gained through the experiments conducted within this dissertation will allow dynamic models of the human partner to be derived. Within the conceptual framework potential models for motor control and decision-making have been mentioned. These should be elaborated based on simulations and experimental studies. When first dynamic models are derived, their implementation on a robot allows for a systematic variation of parameters within psychological experiments. This opens new ways of experimental control, which will lead to further insights into haptic collaboration. For a successful implementation of a robotic assistance in the tracking task reported here, see e.g. Feth et al. [2011].

So far, the analysis of efficiency and dominance focused on average behavior per interaction sequence, which provided valuable insights on causal influences between the feedback provided and the need to negotiate intentions on resulting efficiency of task execution and dominance distributions. However, the acquired data enables extending these analyses by applying time series methods. Therein, one focus in future work could lie in quantifying the information transmitted via mutual haptic feedback.

Even though this dissertation had the clear goal to support the development of robotic partners in haptic collaboration, the relevance of the experimental setup for social studies became also evident. Dynamic models of social behavior have gained more attention recently. However, data-acquisition is still challenging and mainly based on questionnaires. The experimental setups proposed here offer continuous behavior measurement, experimental control of the connection between partners, and manipulation of individual task goals. This enables an investigation of generic rules in social interaction.

A Working Definitions

Adaptation: the capability of a system to adapt towards an environment. Different definitions can be found in theory of evolution, control theory or physiology. Here, the focus is on a general definition appropriate to describe human behavior. Adaptation is "a general term for any process whereby behaviour or subjective experience alters to fit in with a changed environment or circumstances or in response to social pressure" [Colman, 2009].

Collaboration is a specific type of interaction. Different interactions are distinguished in dependence on the intentions of the two (or more) partners / systems. If intentions are shared, the interaction is called collaboration and involves communication. In literature collaboration is also called cooperation [Grosz, 1996] or joint action. Joint actions are defined as a form of *social interaction* where "two or more individuals coordinate their actions in space and time to bring about a change in the environment" [Sebanz et al., 2003a]. In Basdogan et al. [2000] collaboration is divided into simultaneous and sequential interaction. The first one is defined as cooperative action, the latter as collaborative action by Broll [1995]. Another author who distinguishes between the two constructs is Parker [2008]. There, interaction to achieve different individual goals of the partners is called collaboration, whereas interaction for the achievement of shared goals is cooperation. Still, most authors use the constructs collaboration, cooperation and joint action interchangeable and then clarify there focus of investigation further. Here, the three constructs are considered synonymous. Collaboration requires sharing goals and therefore the consideration of intentions. Hence, when two (or more) systems collaborate, the partners share at least one goal and are confronted with the challenge to find a suitable action plan for each system. According to Sebanz et al. [2003a] the following three steps are involved: (a) sharing representations, (b) predicting actions of the partner and (c) integrating the predicted effects. Thus in collaboration, intentions are the origin of information, which we would like to communicate to allow our partner to infer our intentions and jointly form action plans.

Communication relates to the exchange of information as "a process involving two information-processing devices. One device modifies the physical environment of the other. As a result, the second device constructs representations similar to representations already stored in the first device" [Sperber and Wilson, 1998]. Information is explicitly not physical. But it can be transported via physical signals. Hence communication can be defined as "the exchange of meanings between individuals through a common system of symbols" EncyclopediaBritannica [2010]. Communication is based on mutual influence between both systems, thus interaction. But, here a cognitive component, able to process information and its meaning is obligatory.

Decision making is generally defined as the act of choosing one available option out of several which have different trade-offs between benefits and costs. Some researchers refer to the "forming of intentions before acting" [Hardy-Vall?e, in press] whereas others define the exact time-point as decision [Hoffman and Yates, 2005]. However, there is accordance that decision making is a high cognitive skill. In **shared decision making** the interaction partners have a shared goal, but the environment proposes several options how to achieve it. Because of a different information base the individuals may prefer different options. Shared decision making is the interactive process to agree on one option/action plan to reach the shared goal. This requires the recognition and integration of the partners' intentiosn i.e. building a mental model of decision statse requires communication between the two partners. Thus, shared decision making is one form of collaboration. For an overview on shared decision making see Castellan [1993].

Haptics is a term describing one part of the human sensory system. There are two subsystems involved in haptic feedback: tactile (cutaneous) feedback and kinesthetic (proprioceptive) feedback: The first one gives awareness about stimuli on the skin e.g. temperature, pain and forces. The latter subsystem deals with forces, body positions and movements which are perceived in the joints, the tendons and the muscles [Hayward and Astley, 1996; Klatzky and Lederman, 2002]. In Klatzky and Lederman [2002] active and passive touch are differently defined in dependence of an involved motor system. In this dissertation, the focus is restricted to active kinesthetic collaboration but consider the commonly used term "haptic" as synonym throughout the thesis.

Intentions: Even though, interaction can happen between two non-cognitive systems as e.g. in chemical processes, cognitive processes are often involved: The two systems interact/communicate with certain intentions. Intentions are defined as "states of minds that are usually seen to precede thoughtful action, in striving towards sought-after outcomes" [Lepp?nen et al., 2007]. In Tomasello et al. [2005] it is emphasized that intention involves not only the commitment to pursuit a goal but also an action plan to do so. **Thus, intentions are action plans towards a goal**. But intentions are only thoughts on such actions in contrast to real actions [Taillard, 2002]. Not all actions have to be based on intentions [Davidson, 1980]: unintended behavior is possible (e.g. mistakes) and furthermore there is no distinct matching between actions and intentions: the same action can be done due to several intentions and the other way round [Tomasello et al., 2005]. The two concepts "plan" and "intention" are not strictly separated conceptually in literature, instead both are part of a *hierarchical* organization, where a plan is a higher order intention including lower intentions, described as action plans and their accessible effects on the environments [Bratman, 1987; Heinze, 2003; Taillard, 2002; Tomasello et al., 2005].

Intention recognition is the process of becoming aware of the intention of the partner (system), more technically speaking: to infer from an agent's actions on his intentions and their effects in the environment [Tahboub, 2004]. "Understanding intentions is foundational because it provides the interpretive matrix for deciding precisely what it is that someone is doing in the first place" Tomasello et al. [2005]. The research field on *social cognition* is addressing the key-function of shared minds for interaction, for an overview see e.g. Frith [2008].

Interaction is defined as "relationship between two or more systems [...] that results in mutual or reciprocal influence" [VandenBos, 2007]. Interaction relates to physical signals which are exchanged. To allow interaction, it is a prerequisite that the two involved systems have sensors and actuators, which allow mutual perception, and that the states of one system change in dependence of the other and vice versa.

Learning: change of internal dynamics of a system due to changes from experience EncyclopediaBritannica [2010]. In Colman [2009] it is referred to a *lasting* change in behavior, knowledge and skills based on interaction with the environment and experience. In Richardson et al. [1994] learning is defined as "processes by which people change their mental models".

B Overview-Table of Experimental Studies on Haptic Collaboration

In the following studies, which experimentally investigate haptic collaboration, are summarized. A discussion of the table is given in Section 3. The task and results are challenging to interpret without knowledge on the whole publication. However, the table allows for a fast keyword search. The table is structured by

- **Authors** and References
- Research interest (**RI**): the parameter which are experimentally varied or the general goal, e.g. evaluation of a controller design
- **Interaction** type between collaborating partners: *HRI* refers to human-robot interaction; *HRHI* refers to robot-mediated human-human interaction; *HHI* describes human-human interaction which is not technically mediated. Within this category it is distinguished if the visual feedback of the manipulated object or the point is given in *reality* or in *VR*. If the haptic feedback was manipulated can be derived from a research interest in ”feedback”.
- **Task**: the task which participants had to perform is summarized.
- **Environment** describes the experimental setup, i.e. the used hardware
- **Participants**: informs about the number of participants taking part in the study. Here, *std. p* describes designs where one partner was standardized, meaning that he was part of the experimenter team and interacted with each participant; *dyads* refers to cases where both partners are participants, being part of only one dyad; other designs are described explicitly.
- **Measures**: the analyzed measures are reported (abbreviations: *TOT*: time on target; *TTC*: time to task completion)
- **Analysis**: describes the data analysis by separating knowledge gained by inspection and descriptive statistics *ds* from inference statistic analysis *is*
- **Results**: gives a short overview on the results
- **Level**: reports the level of haptic collaboration which is defined in relation to the conceptual framework introduced in Chapter 2: Low level collaboration focuses on intention negotiation *how* to move an object/interaction point, whereas high level collaboration deals with intention negotiation *where* to move an object/interaction point.

Table B.1: Experiments on Haptic Collaboration (with quantitative analysis)

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Allison et al. [2004]	feedback, delay	HRHI, VR	point task maintaining constant interaction force between partners	3 DoF custom-made robots but only 1 DoF used; in the haptic condition there is no vision, simulated spring between end-effectors	12 with std. p.	TTC, position errors, inverse TOT	ds	performance worse with increased delay in both feedback conditions; participants were faster with visual feedback	low
Arai et al. [2000]	evaluation	HRI, real	planar movement of aluminum pipe to target position	7 DoF industrial robot (PA-10, MHI): 6 DoF at wrist and a gripper	1	comparison of object trajectories resulting from different assistance algorithms by inspection, observation of side-slips at robot gripper	ds	assistance method using non-holonomic constraint leads to smoother object trajectory compared to method based on impedance control; when the operator can apply only translational forces, the non-holonomic constraint algorithm suppresses side-slips at the robots gripper (method is extended to three dimensional movements in Takubo et al. [2002])	high
Bakar et al. [2006]	dominance	HHI, real	1 DoF vertical motions	object with 3D position camera system and force sensors	5, all possible combinations	questionnaire for participants instructed to represent ”slaves” on task difficulty	ds	participants divided into master and (blind-folded) slave group, two object weights, three speed values and two motion trajectories (20cm and 40cm), heights of master and slave (standing on a box), up or downward movements are distinguished: fast movements are easier to detect, even more if heights between master and slave varies	low
Bakar et al. [2009b], see also Bakar et al. [2008, 2007, 2009a,c]	dominance	HHI, VR	1 DoF pointing task	object with force and LED (position) sensor, monitors	20 = 10 dyads	force and velocity profiles, TTC, position error	ds	when the follower knew the target position of the object his/her motions were smoother than when this information was not given	low
Basdogan et al. [2000]	feedback	HRHI, VR	path following: ring on wire game	2 PHANToMs	10 with std. p.	TTC , TOT, questionnaire on presence and togetherness	is	performance better with haptic feedback, togetherness increased with haptic feedback compared to no-haptic-feedback condition	low
Corteville et al. [2007]	evaluation	HRI, real	1 DoF pointing task	linear actuators	1	forces	ds	interaction force is reduced by about 50N when a 75% assistance is given	low

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Esen et al. [2007]	evaluation, feedback	HRHI, VR	medical bone-drilling training	two ViSHaRD10 hyper-redundant haptic displays; conditions: no training, verbal tutoring by trainer, force demonstration to student, force/velocity leading by tutor	4*8 with std. p.	performance: multi-dimensional Euclidean distance measure between trainer and student in force, velocity and time	ds	learning effect descriptively strongest with verbal tutoring, followed by force/velocity leading and force demonstration	low
Evrard and Kheddar [2009]	dominance	HRI, VR	pointing task including obstacle avoidance;	PHANToM	1	plots of lifting altitude (position), forces	ds	after introducing a leader-follower-metrics, two different leader-follower sequences within the motion were compared: no force-specialization was found	high
Fernandez et al. [2001]	evaluation	HRI, real	transport a 2m rigid object around the corner in a corridor	mobile manipulator (not specified further)	1	position trajectory, forces	ds	it is concluded that the intention recognition (HMM) based active-coordination-module allows cooperative following behavior of the robot; though, at this state behavior is not robust enough	high
Feth et al. [2009b]	partner, feedback	HRHI, VR	1 DoF tracking task	two linear actuators; in the visual condition there is no force feedback from the partner, only from the object	24 = 12 dyads	position error, forces, energy	is	performance increased in dyadic condition; evidence for energy flow between partners found	low
Feth et al. [2009a]	partner, feedback, model	HRHI, VR	1 DoF tracking task	two linear actuators	12 = 6 dyads	position error, forces	is	McRuer's model for individual tracking behavior explained the empirical data in this task and was extended for dyadic behavior; individuals within a dyad behave not in accordance with this model	low

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Feth et al. [2009c]	evaluation, feedback, partner	HRHI, VR	joint 2 DoF pointing task	jointly manipulated tele-robot with two masters (all admittance-type haptic input devices with 6 DOF)	26 = 13 dyads	position error and TTC	is	comparison of three conditions: single operator, two operators either with or without mutual force feedback; conditions did not influence error, but task completion time was significantly decreased with haptic feedback compared to other two conditions, no difference in individual and visual feedback condition	high
Gentry and Murray-Smith [2003]	dominance	HRHI, real	following ”dancing moves” led by robot	PHANToM, without object, no visual feedback from task	5	position errors by inspection	ds	misclassification of dance steps can be identified , evidence for haptic signals found	low
Gentry et al. [2003]	dominance	HRHI, real	following in dancing with human or robot	PHANToM	6 with std. p.	errors by inspection	ds	no performance differences between human and robot leader	low
Gentry et al. [2005]	partner	HRHI, real	rotational pointing task	wheel with two handles	5 all possible dyad combinations	TTC, errors	ds	Schmidt's law predicts the relation between task difficulty and TTC; dyads made more errors than individuals but moved faster.	low
Glynn et al. [2001]	feedback, delay	HRHI, VR	2 DoF tracking task in maze	two studies: a) second order system, b) zero-order; joysticks	a) 22 dyads; b) 24 dyads	TTC, position error; coordination measure = zero-lag cross correlation between input	is	a) less errors without force feedback, lower position error, no difference in TTC; b) with force feedback faster and with lower position error, damage identical; team coordination was better with haptic coupling; delay leads to higher TTC and damage, no difference in position error	low
Goncharenko et al. [2004]	partner, model	HRHI, VR	1 DoF rotational movement (without target)	two PHaNToMs	1	force and force-derivative profiles	ds	movements can be predicted by force-change-based criterion rather than by force-based criterion	low
Groten et al. [2009b], compare Section 5.2	feedback, partner	HRHI, VR	1 DoF tracking task	two linear actuators	24 = 12 dyads	position error, forces, power, efficiency	is	comparing conditions where the tracking task is executed alone / with partner and force feedback only from the object / partner and force feedback between partners: interaction increases performance; haptic feedback between partners cannot be considered efficient as performance does not increase further but interaction effort increases	low

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Groten et al. [2009a], compare Section 6.3	feedback, dominance	HRHI, VR	1 DoF tracking task	two linear actuators	24 = 12 dyads, round robin design	forces, dominance	is	haptic feedback between partners is compared to a condition without such feedback: in both cases the dominance distribution between partners is unequal; haptic feedback leads to higher consistency in dominance behavior across partners	low
Groten et al. [2010], compare Section 5.3	feedback	HRHI, VR	1 DoF tracking task with binary decision making	two linear actuators	32 = 18 dyads	position error, power, efficiency	is	with increased need of haptic negotiation (different preferences in individual decisions) haptic feedback between partners leads to higher performance; compared to a visual partner feedback condition no difference in efficiency was found as the effort (power) increases as well	high
Hamza-Lup et al. [2009]	delay	HRHI, VR	stack cubes by lifting and maneuvering	two "haptic devices"	22 (no further information)	TTC, errors	ds	increased delay leads to worse performance	high
Hirata et al. [2005a], see also Hirata et al. [2003, 2007, 2008]; Nejatbakhsh and Kosuge [2005, 2006]	evaluation	HRI, real	path following (s-shaped) with walking support system	WalkingHelper prototype robot	9	integrated error between desired and actual path	ds	maneuverability of system is improved by proposed control law	low
Hirata et al. [2002], see also Hirata and Kosuge [2000]; Hirata et al. [2001,b, 2002]; Sato and Kosuge [2000]; Seto et al. [2007]; Suda et al. [2003]	evaluation	HRI, real	move large object along a path with robot assistance	two passive mobile robot PRP	1	difference between actual and desired path	ds	distributed motion control algorithm leads to smaller deviations compared to non-distributed algorithm	low
Ikeura et al. [2002]	evaluation	HRI, real	1 DoF pointing task	6 DoF Robot (PUMA 562)	15	questionnaire on movability, ease of position, stability and human-likeness	is	comparison of 3 different impedance controllers (constant low, constant high, variable) for robotic partner: variable impedance controller is perceived better in easiness of positioning and stability than constantly low impedance; the variable controller outranges the high constant impedance controller in movability and human-likeness	low
Ikeura et al. [1997]	dominance, model	HHI, real	carried object with force sensors; laser sensors to track object position	1 DoF pointing task	2 = 1 dyad	force, velocity, energy	ds	if the follower is blindfolded he/she can be described with variable damping control model, coordination is considered more efficient the more passive the follower	low

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Khademian and Hashtrudi-Zaad [2007a]	dominance	HRHI, VR	path following (square),	3 DoF planar twin Pantograph jointly control virtual slave, only the trainer has visual feedback	6 (trainee) with std. p. (trainer)	error	ds	different dominance distribution values between partners introduced (0, 0.25, 0.5, 0.75, 1: dominance sharing ($\neq 0, 1$) increases performance of trainee compared to full control by trainer	low
Khademian and Hashtrudi-Zaad [2009a]	evaluation, dominance	HRHI, VR	move a salve robot along an oval virtual path	2 Quansar 3 DoF planar twin Pantographs and a simulated model of this device as the jointly manipulated virtual slave	6 (trainees) with std. p. (trainer)	questionnaire on sense of environment, maneuverability, guidance by trainer (not described in detail)	ds	three control architectures a) weighted sum of position and force between two operators depending on α, b) same as 1 but also with α = 0 or 1 the non-dominant user receives feedback, c) constant stiff connection = equal positions regardless of α) crossed with three different levels of dominance ($\alpha = 0, 0.5, 1$): architecture a) leads to higher sense of environment, b) leads to better guidance and maneuverability	low
Khademian and Hashtrudi-Zaad [2009b]	evaluation, dominance	HRHI, VR	move a slave robot along a square path	2 Quansar 3 DoF planar twin Pantographs and a simulated model of this device as the jointly manipulated virtual salve	5 (trainees) with std. p. (trainer)	TTC, error, energy	is (not reported in detail)	comparing effects of viewpoint, environmental mushiness, virtual fixtures and dominance distribution between partners (not fully crossed factorial design) shows that dominance is not influencing the measures, higher mushiness and virtual fixtures lead to lower TTC and higher energy	low
Kim et al. [2004]	feedback	HRHI, VR	jointly lift a virtual cube for as long as possible	two PHaNToMs	20 with std. p.	questionnaire on subjective performance, and (co-)presence	is (not reported in detail)	haptic feedback increases co-presence, no information on performance is given	low
Kosuge and Kazamura [1997]	evaluation	HRHI, real	2 DoF tracking task	industrial robot 6 (DoF) with pen	”several”	participants’ comments, intentional forces, inspection of robot behavior	ds	comparison of damping and impedance controller: with lower damping coefficient in damping controller the motion of the pen is less smooth but more accurate	low

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Maeda et al. [2001]	evaluation	HRI, real	1 DoF transportation of object	6 DoF JS2	two studies: a) 1; b) 3	velocity profile, energy	ds	a) motion estimation (based on minimum jerk model) leads in the authors' opinion to more human-friendly manipulation; b) motion estimation reduces unnecessary energy	low
Mateo et al. [2005]	partner, delay	HRHI, VR	pointing task	PHANToM	2 best and 2 worst performers out of 7 individuals = 4 dyads	TTC	ds	with partner and increased delay: performance decreased	low
Miossec and Kheddar [2008]	partner, model	HHI, real	lift object from one position to another	real object: object in individual condition had half the weight as in dyadic condition	3 dyads	position and velocity trajectories	ds	minimum jerk model not verified, tendency to average the alone behavior in dyadic trials	high
Mulder et al. [2008]	feedback, evaluation	HRI, VR	driving in simulation	fixed-based driving simulator with pedals and actuated steering wheel and virtual driving scene; either haptic guidance (based on deviation between reference path and future position of vehicle) or no guidance was provided	12	performance: RMS, control activity: standard deviation in steering wheel angle; control effort: standard deviation in steering forces	is	performance is increased, control activity decreased but effort higher with haptic guidance	low
Nudehi et al. [2005]	evaluation	HRHI, no vision	trainee had to imitate mentor's actions	two identical wrists, each with 2 DoF along the horizontal and vertical axes	1 dyad	force tracking (imitation) error by inspection	ds	two controllers were compared, one led to a descriptively smaller error; the goal to show that it is possible to design multiple candidate controllers is reached	low
Oakley et al. [2001]	feedback	HRHI, VR	dyadic computer programming	PHANToM, monitors	8 dyads	TTC, questionnaire on usability, workload, presence, collaboration	ds	haptic feedback more demanding in terms of subjective workload, leads to higher presence, better usability	high

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Oguz et al. [2010]	dominance, evaluation	HRI, VR	hitting obstacles with a ball on a plane in instructed order with assistance controller	PHANToM Omni	10	questionnaire on performance, human-likeness, collaboration, control (in the sense of dominance); TTC, path length, energy, error	is (not reported in detail)	different assistance modes are compared a) equal control on both axes; b)shared control dependent on user's forces; c) no assistance): performance lowest without guidance, energy highest with equal control, shared control leads to tradeoff between accuracy and energy with high subjective rating	high
Rahman et al. [1999], see also Ikeura and Inooka [1995]; Ikeura et al. [1994]; Rahman et al. [2002b]	dominance, model	HRI, real	1 DoF pointing task	1 DoF robot, force sensor	3	parameter identification of human arm impedance: position, velocity, stiffness, damping	ds	when robot is leading in cooperation the velocity of human and impedance model follows minimum jerk trajectory	low
Rahman et al. [2002a], see also Rahman et al. [2000]	dominance	HRHI, real	1 DoF pointing task	linear motor, two force sensors	10, all possible dyad combinations	forces, acceleration, correlation	ds	one participant is always leading and the other following	low
Reed et al. [2004]	partner	HRHI, real	rotational pointing task	1 DoF two-handled crank, inertia doubled in dyadic trials	4 dyads	TTC	ds	faster performance for dyads than individuals	low
Reed et al. [2005], compare also Reed and Peshkin [2008]	partner	HRHI, real	1 DoF rotational pointing task	two-handled crank, inertia doubled in dyadic trials	56 = 28 dyads	TTC, forces	ds	no specialization in movement direction but partly acceleration-deceleration specialization was found; steady dyadic opposition forces found	low
Reed et al. [2006], compare also Reed and Peshkin [2008]	partner	HRHI, real	1 DoF rotational pointing task	two-handled crank, inertia doubled in dyadic trials	30 =15 dyads; 11 with robot	TTC, forces	ds	dyads faster than individuals, dyadic specialization: deceleration and acceleration, higher forces in dyads (*2.1); force profile when interacting with robot similar to individual profile	low
Reed et al. [2007], compare also Reed and Peshkin [2008]	partner	HRHI, real and HRI, real	1 DoF rotational pointing task	two-handled crank	22= 11 dyads	TTC participants' comments on partner	is	Turing test (replay trajectory for robotic partner): human dyads perform better than individuals but human-robot teams do not; robot not recognized as such	low
Sallnäs et al. [2000]	feedback	HRHI, VR	stacking of virtual cubes in given patterns, moving along the cubes	PHANToM, participants were allowed to talk	14 dyads	questionnaire on performance, (co-)presence, TTC	is	no difference in co-presence, TTC better, presence higher and perceived performance higher with haptic feedback	high
Sallnäs [2001]	feedback	HRHI, VR	stacking cubes and putting them in a given order	PHANToM, participants were allowed to talk	14 dyads	video analysis: errors	is	explains results from Sallnäs et al. [2000]: without haptic feedback TTC was higher, because significantly more cube-lifting failed	high

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Sankaranarayanan and Hannaford [2008a]	evaluation, delay	HRHI, VR	object has to follow target in 1 DoF movements	Omni haptic device , the object provides color cues on interaction forces between users	10 with std. p.	position error, forces	is (not reported in detail)	comparison of three different controllers to handle time delay in telepresent setup: tuned pd, wave variable and time domain passivity controllers: pd-controller was best in terms of position error and wave variable based approaches in terms of forces	low
Sankaranarayanan and Hannaford [2008b]	evaluation	HRHI, VR	object has to follow target in 1 DoF movements	Omni haptic device , the object provides color cues on interaction forces between users	18 with std. p.	position error, forces	is (not reported in detail)	three transmission rates (100, 500, 1000 Hz) and three virtual coupling shemes (rigid, local, central) between users and four delay conditions where evaluated (factorial design not fully crossed): performance with central coupling is best, but rigid coupling is preferred	low
Schaußet al. [2010]	evaluation	HRHI, VR	pick and place of real object (multi-user telepresence)	masters: two haptic interfaces (4 DoF); slaves: two tele-operator arms with 4 DoF	20 = 10 dyads	TTC, forces, efficiency	is	comparison of assistance controllers: pure damping of the individual movements does not increase performance, but increases effort (forces) whereas the introduced damping based virtual coupling increases both	high
Solis et al. [2007]	evaluation	HRI, VR	learn writing of Japanese characters	pen-stylus designed by PERCRO, Monitor, comparing intention recognition based guidance using hidden Markov model (HMM) to classical guidance	10	TTC, force, recognition rate by HMM in % comparing it to traing session results	is (not reported in detail)	the assitance recognized Japanese letters correctly in 81% of cases and provided assistance in 56%; howvever, performance was not increased compared to classical guidance	high
Takeda et al. [2007a], see also Nakayama et al. [2009]; Sakai et al. [2007]; Takeda et al. [2005, 2007b,c]	evaluation	HRI, real	ballroom dance	MSDanceR with force/torque sensor in waist	3	success rate if dance steps are recognized	ds	based on hidden Markov models the robot should estimate the human leaders intention to dance the correct steps: success rate between 50% and 98.88%, higher than with neural network control in previous studies Hirata et al. [2005b]	high

Authors	RI	Interaction	Task	Environment	Participants	Measures	Analysis	Results	Level
Ueha et al. [2009]	partner, dominance, evaluation	a) HHI, VR; b) HRI,VR	1 DoF rotational pointing task	two handed crank and a 5DoF (only 3 used) robot arm	a) 16 = 8 dyads; b) 1	TTC, forces	ds	a) dyads perform faster with partner than alone; participants are either responsible for radial or tangential forces; b) separation of tangential and radial forces in a Turing test where robot is applying radial forces increases performance	low
Ullah et al. [2010]	feedback, evaluation	HRHI, VR	peg-in-hole task	two string based parallel robots, screen, 3 DoF movements, four haptic guide conditions: a) spring towards object, b) speed coordination c) simple force feedback from cylinder, d) no force feedback	10 with std. p.	performance: TTC, detachment from cylinder, subjective rating, co-presence	is (not reported in detail)	simple force feedback led to best performance and subjective rating, co-presence highest with speed coordination	high
Wang et al. [2009]	evaluation	HRI, real	active and passive handshaking with robot	10 DoF robotic arm (ViSHaRD10)	training: 4; evaluation: unknown	position and force trajectories	ds	the handshake is realized with a position-based admittance controller and an additional HMM controller estimating human intentions (active vs. passive handshake): artificial handshake trajectory resembles reference trajectory and interaction forces decrease with interaction	low
Wojtara et al. [2008, 2009]	evaluation	HRI, real	positioning flat object at target position	6 DoF robot prototype	3	TTC, error	ds	comparison of three different algorithms (DoF separation between human and robot, weighted control of DoFs, robot following algorithm) shows that with following algorithm accuracy is highest	high

C Control Architecture and Parameters of Haptic Interfaces

C.1 Control Architecture

In Figure C.1 the control architecture for the virtually coupled linear devices as employed in the experiments is depicted. Due to the high gain PD-controller (compare Table C.1), a rigid connection between the two partners in this mutual haptic feedback condition can be assumed. The admittance resembles the virtual object which is rendered as a inertial mass only. Thus, the related transfer function is

$$G_o(s) = \frac{X_o(s)}{F_{sum}(s)} = \frac{1}{ms^2}. \quad \text{(C.1)}$$

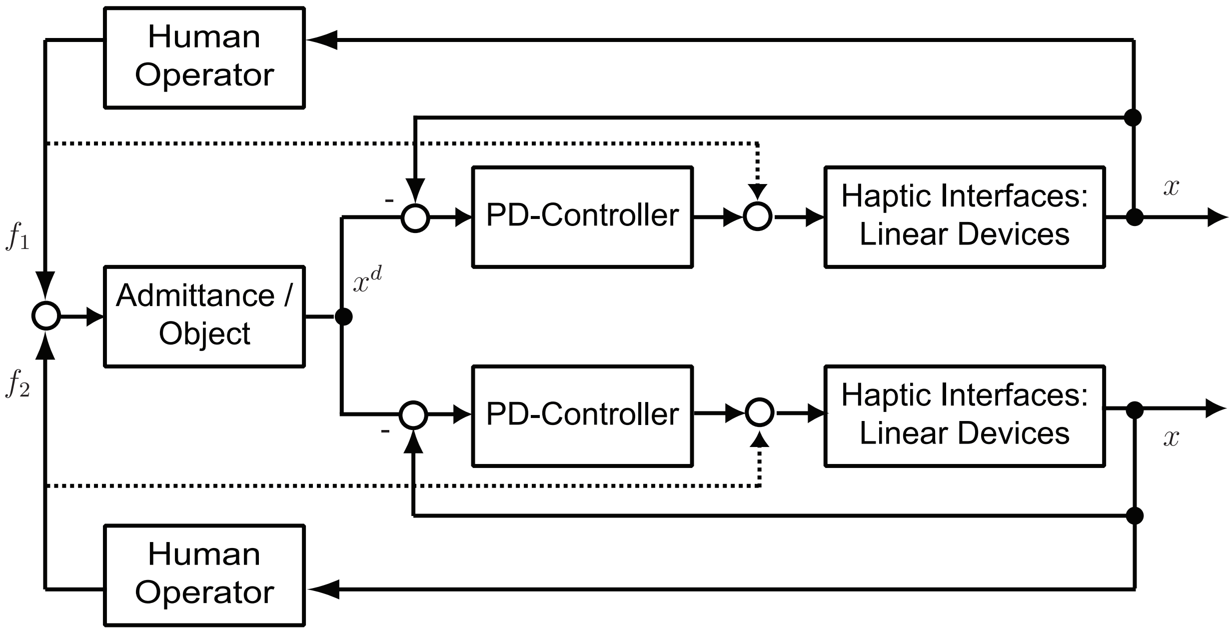


Figure C.1: Control architecture for both linear devices used in the experimental setup described in detial in Section 4.2.4. Here, the mutual haptic feedback condition is depicted.

C.2 Parameters

The parameter values for the above shown architecture, which is used to realize the experiments in this dissertation, are listed in Table C.1.

Table C.1: Parameter values of PD-controller and the mass of the admittance. The value of the inertial mass is set to 20kg except for one “alone conditions” in the experiment conducted on intention negotiation in low-level haptic collaboration (compare Sections 4.2.3 and 5.2).

Parameter	Value
k_p	70000 N/m
k_d	530 Ns/m
m	20kg (10kg)

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