Haptic Role Allocation and Intention Negotiation in Human-Robot Collaboration

by

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To mom and dad

ABSTRACT

This dissertation aims to present a perspective to build more natural shared control systems for physical human-robot cooperation. As the tasks become more complex and more dynamic, many shared control schemes fail to meet the expectation of an effortless interaction that resembles human-human sensory communication. Since such systems are mainly built to improve task performance, the richness of sensory communication is of secondary concern. We suggest that effective cooperation can be achieved when the human's and the robot's roles within the task are dynamically updated during the execution of the task. These roles define states for the system, in which the robot's control leads or follows the human's actions. In such a system, a state transition can occur at certain times if the robot can determine the user's intention for gaining/relinquishing control. Specifically, with these state transitions we assign certain roles to the human and the robot. We believe that only by employing the robot with tools to change its behavior during collaboration, we can improve the collaboration experience.

We explore how human-robot cooperation in virtual and physical worlds can be improved using a force-based role-exchange mechanism. Our findings indicate that the proposed role exchange framework is beneficial in a sense that it can improve task performance and the efficiency of the partners during the task, and decrease the energy requirement of the human. Moreover, the results imply that the subjective acceptability of the proposed model is attained only when role exchanges are performed in a smooth and transparent fashion. Finally, we illustrate that adding extra sensory cues on top of a role exchange scheme is useful for improving the sense of interaction during the task, as well as making the system more comfortable and easier to use, and the task more enjoyable.

ÖZETÇE

Bu tezin amacı, insan ve robotların dahil olduğu fiziksel işbirliği süreçleri için doğal bir ortak kontrol sistemi kurulmasını sağlayacak bir bakış açısı geliştirmektir. Robotların insanlarla beraber tamamlamaya çalıştığı görevler karmaşık ve dinamik hale geldikçe, insan-insan iletişimine benzer mekanizmalar ile iletişim sağlama ihtiyacı doğmaktadır. Ancak, varolan sistemlerin çoğu, çok kipli iletişimin zenginliğinden çok performansı iyileştirmeyi hedeflemektedir. Bu tezde, insan ve robot arasındaki iletişimin, robotun, insanın niyetini algılayıp kendi kontrol seviyesini dinamik olarak ayarlayabildiği bir karar verme süreci sayesinde geliştirilebileceği öne sürülmektedir. Bu amaçla, lider ve takipçi rolleri tanımlanmış ve partnerlerin sadece kuvvet kanalı aracılığıyla anlaşarak rollerini dinamik olarak değiştirmeleri sağlanmıştır.

Amacımız, insan-robot işbirliğinin kuvvet tabanlı bir rol değişim mekanizması ile sanal ve fiziksel dünyada nasıl geliştirilebileceğini araştırmaktır. Bulgularımız, rol değişimi içermeyen bir “eşit kontrol” durumu ile karşılaştırıldığında, rol değişim mekanizmasının görev performansını ve ortak verimliliği geliştirdiğini, aynı zamanda insanın görev boyunca harcadığı enerjiyi düşürdüğünü işaret etmektedir. Bunun yanında, bahsi geçen faydaların, bu mekanizma akıcı ve saydam bir şekilde programlandığında belirgin olarak ortaya çıktığı görülmüştür. Son olarak, etmenlerin rol dağılımlarını kullanıcılara farklı duyusal kanallar yardımıyla göstermenin, etmenler arası etkileşim hissiyatını arttırdığı, sistemi daha rahat ve kolay kullanılır hale getirdiği ve görevi daha eğlenceki kıldığı görülmüştür.

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NOMENCLATURE

ANOVA	Analysis of variance
df	Degrees of freedom
DoF	Degrees of freedom
FB	Feedback
HHI	Human-human interaction
pHHI	Physical human-human interaction
HRI	Human-robot interaction
pHRI	Physical human-robot interaction
SD	Standard deviation
SEM	Standard error of means
IQR	Interquartile range
VR	Virtual reality
RE	Role exchange
VHC	Role exchange with Visuo-Haptic Cues
NG	No Guidance
EC	Equal Control
RA	Role allocation
PRA	Proactive role allocation
CRA	Constant role allocation
DPRA	Discrete proactive role allocation
WPRA	Weighted proactive role allocation

Chapter 1

INTRODUCTION

The research presented throughout this dissertation aims at building intelligent robotic agents that can proactively cooperate with humans under joint action in virtual and physical worlds. In particular, we discuss the necessary components that enhance various aspects of haptic man-machine interaction in highly dynamic collaborative tasks. In the rest of this dissertation, we will present an extensive summary of the set of experiments we have done to enable haptic role allocation in joint manipulation tasks performed in collaboration with a robot.

1.1 Problem Definition and Approach

Ideally, we aim at building a robot that can intuitively and naturally share control with a human during physical cooperation. Even though robots have been programmed to share control with humans in order to increase performance or smoothness, interaction with such robots is still artificial when compared to natural human-human collaboration.

Collaboration requires partners to actively adapt to changes in one another's requirements and construct a shared knowledge base about the operations and intentions of each other (Dourish and Bellotti, 1992). We, humans, have great intuitive ability to realize this adaptation when working with other humans. We are capable of communicating through many modalities, tacitly expressing our intentions, and understanding those of our partner through nonverbal communication. During joint manipulation tasks (e.g. the joint transportation of a heavy object), we can instantly understand our partner's capabilities, such as his/her being strong, and personal traits, such as being submissive. Depending on how we think our partner will behave during the task, we typically change our behavior. This process is interconnected with defining implicit roles during the task, such as being the follower, the leader, the weight-bearer, or the decision maker of the task; and these come along with a continuous process of negotiating about the roles we take.

Unfortunately, only little research exists on allocation and adaptation of roles in physical human-robot interaction. In order to develop a robotic partner that can adapt to a human in an ongoing collaboration, we bring forward the necessity of a situation-dependent dynamic role allocation between partners. In physical cooperation, two humans communicate dominantly through forces for negotiating action plans for accomplishing a task. However, in the context of human-robot interaction, communication through the haptic channel has not yet been explored in sufficient detail. We suggest that as the robots are being more capable of performing a broader variety of tasks, more sophisticated robotic partners, which can recognize and respond to force signals acquired from the humans, should be built.

In cooperation involving haptics, the coupling between the human and the robot should be defined in a way that the robot can infer the intentions of the human operator and respond accordingly. In this regard, we suggest an intention recognition system, in which a robot can infer the human's intentions in a dynamic collaborative task using only force information. In response to the recognized intentions, the robot changes the amount of its participation within the task, which constitutes a role exchange framework for human-robot interaction (also see (Oguz et al., 2010; Kucukyilmaz et al., 2012; Moertl et al., 2012)). The proposed role exchange framework allows negotiation through the haptic channel, thus serves to communicate the cooperating parties dynamically, naturally, and seamlessly.

Additionally, we suggest that the interaction experience can be further enhanced if the state of interaction is explicitly conveyed to the human operator. In order to achieve this, informative cues, in various forms and through multiple modalities, can be used to signal the interaction state (also see (Kucukyilmaz et al., 2011, 2013)).

Although displaying arbitrary combinations of such cues may hamper communication if perceptive or cognitive conflicts arise in the process (McGee et al., 2001), an effective combination of these cues can be beneficial. Even though existing studies demonstrate that the use of multiple modalities improves interaction in virtual environments (Díaz et al., 2006), to our knowledge, our study in (Kucukyilmaz et al., 2011) have been the first to utilize multimodal feedback to inform the users on different states of the system to facilitate collaborative interaction through the haptic channel. We show that additional modalities, when carefully displayed on top of a role exchange mechanism, help building a subjectively more pleasing collaboration experience.

1.2 Applications

We believe that in a collaborative system, the human and the robot need to partition the task into units to get maximum benefit from each other's abilities. In general, it is assumed that humans are good at tasks that require perceptual and cognitive processing, and benefit greatly from prior knowledge. On the other hand, robots are widely accepted to be superior in tasks that require precision and accuracy. Hence, we believe that a collaborative scheme will yield the best results if it successfully divides the labor of the robot and the human regarding their strong abilities and dynamically let each party to take control in appropriate moments during the task. For example, Subasi and Basdogan (2008) illustrate a good example of human-robot collaboration in molecular docking. In their application, the human operator manipulates a small molecule in a virtual environment through a haptic device to search for the true binding cavity on the surface of a large molecule. Once the binding site is discovered, the robot takes over the control and fine-tunes the alignment of the molecule inside the cavity. In this sense, physical human-robot interaction, computer aided design, simulation-based medical training, rehabilition/home robotics, and interactive games can be listed as potential applications for schemes that implement different roles for human and robot partners.

1.3 Contribution

In our studies, we investigated objective and subjective benefits of dynamic haptic role allocation for dyadic interaction. We focused on cooperative shared control tasks in virtual and physical scenarios, where a human interacts with a robotic entity. In order to realize dynamic role allocation, we programmed the robot to be able to change its role (i.e. the control level) within the task by observing the force input of the human it interacts with. In order to display the benefits of the proposed role exchange (RE) mechanism, we designed different experimental setups that allow a comparison of different role allocation strategies in virtual human-computer interaction (HCI) (see Kucukyilmaz et al. (2011, 2012, 2013); Oguz et al. (2010)) and physical human-robot interaction (pHRI) scenarios (see Moertl et al. (2012)). We suggested different quantitative metrics to evaluate task performance, efficiency, and human effort, as well as qualitative scales to evaluate the subjective acceptability of the proposed framework. Using these metrics, we compared the performance of the dynamic RE mechanism with that of a static role allocation scheme, in which the robot does not display proactive behavior.

In preliminary studies, we observed that the RE mechanism presents the users with an option to choose and optimize between accuracy and energy when the users are not given any information on how to use the underlying mechanism (also see (Oguz et al., 2010)). Later, we conducted a controlled user study, in which we initially explained the RE mechanism to the users and evaluated their performance afterwards. The results of this user study suggest that the proposed RE mechanism improves task performance when compared to the equal control guidance scheme (EC). Also, we observed that the efficiency of the users and the joint efficiency of the dyad are significantly higher under RE[1]. This implies that the users accomplish a higher amount

[1]Note that the collected data contained outliers, which are addressed before analyzing the data. The trends in our results remain intact regardless of whether we apply outlier elimination or not. In case no outliers are eliminated, we fail to observe any statistically significant differences between the performances achived under different experimental conditions. On the other hand, the conclusions about the efficiency do not change.

of work with less effort when they are capable of exchanging roles with the robot (also seeIn (Kucukyilmaz et al., 2013)). This result shows that the users can effectively benefit from a role exchange mechanism when they are explicitly instructed on the principles of interacting with the robot.

Additionally, we sought the benefits of supplementing the system with additional visual and vibrotactile haptic cues to inform the users on the control state regarding the negotiation process. With the integration of these cues (VHC), we observed that task performance deteriorates, probably due to an extra cognitive load introduced by these cues. However, subjectively, the users reported that these additional cues make the interface of the system easier to use, the task more interactive, and their robot partner more trusted. Under both RE and VHC, we observed that the movement of the ball is predominantly controlled by the robot. Moreover, the role exchanges are performed at similar instants during the task and their numbers were close under both conditions. However, without the additional cues (under RE), we observed that the users incorrectly think that they held control of the ball more often then they did under VHC (also see (Kucukyilmaz et al., 2013)). This is a sign that additional cues are helpful in conveying the control state to the users.

Finally, we illustrated that the proposed mechanism can also enhance the assistive capability of a robotic partner in physical cooperation with humans. In a controlled user study, we compared between different implementations of the dynamic role exhange policy. Our evaluation revealed that dynamic role exchange is superior over a constant role allocation strategy only when it is realized in a continuous fashion, whereas the human partners subjectively prefer constant role allocation, during which the behavior of the robot is obviously more predictable (Moertl et al., 2012).

1.4 Outline

This dissertation is organized as follows: In Chapter 2, we present an extensive summary of the related work on role allocation and control sharing in HCI and HRI scenarios. In Chapter 3, we present two experimental studies that investigate the utility of the proposed role exchange approach in haptics-enabled virtual collaboration tasks: The first experiment (Section 3.3) explores the case, in which the users of the system do not know about the underlying RE mechanism. On the other hand, the second experiment (Section 3.4) focuses on the scenario, where the users are explicitly informed about REs and are trained with the system beforehand. Chapter 4 presents the use of the RE mechanism in a physical interaction scenario with a man-sized mobile robot. Finally, Chapter 5 elaborates on the results and Chapter 6 revisits our contributions and suggests possible future directions.

Chapter 2

RELATED WORK

This chapter presents related work on control sharing and roles in haptic collaboration and presents background on cooperative load sharing for physical human-robot interaction.

2.1 Control Sharing and Roles in Haptic Collaboration

The idea of haptic cooperation emerged in the early 60's. In early telerobotics systems, control was shared between humans and computers (i.e. robotic agents) for automation purposes, where the human acts as a supervisor (Sheridan, 1992). An alternative to supervisory control was introduced by Bernstein (1967), who suggested that human motion can be controlled to adapt to certain restrictions applied on it. This idea was later implemented by Rosenberg (1993) as a guidance scheme under the name of "virtual fixtures". However, the original implementation of this approach was prone to conflicts when the users failed to obey robotic guidance; also it was inefficient in training, since it generally made the users depend too much on guidance.

Haptics has been widely used to implement guidance in training applications, where the main goal is to teach the trainees the dynamics of the task (e.g. Groten et al. (2010); Powell and O'Malley (2011); Oakley et al. (2001); Moll and Sallnäs (2009); Morris et al. (2007); Feygin et al. (2002)). Also, cooperative shared control schemes were developed for haptic systems, where humans and robotic agents share the control of a system to collaborate towards a common goal. However, human-human cooperation is far richer and more complex than simple shared control: The roles and the control levels of the parties on the task are dynamically variable and intentions are conveyed through different sensory modalities during the execution of the task. Moreover, negotiation is a significant component of interaction in human-human cooperation. Shared control systems available today for human-robot cooperation possess only a subset of these features (also refer to (O'Malley et al., 2006) and (Abbink et al., 2012), which present extensive reviews on haptics-enabled shared control systems). Hence, as cooperative tasks get more complex and more dynamic, such guidance schemes fall short in meeting the expectation of an effortless interaction that resembles human-human sensory communication. Since haptic guidance systems are mainly built to improve task performance, the richness of sensory communication is of secondary concern. On the other hand, cooperative systems, where the human and the robot can achieve better performance if only they work together, require a more elaborate design, which allows a richer sensory communication between the partners. More recently, researchers showed that haptic guidance systems can be further improved if they are equipped with predictive and progressive mechanisms (Forsyth and MacLean, 2006; Huegel and O'Malley, 2010; Lee and Choi, 2010).

In order to alleviate the problems caused by strict restrictions on the task, a mechanism, where both parties can be employed with different levels of control during the task, is needed. Sierhuis et al. (2003) reasonably stated that "even highly autonomous systems have a strong requirement for effective interaction with people". In the last decade, interactive man-machine systems with adjustable autonomy have been developed. Adjustable autonomy is implemented to make teamwork more effective in interacting with remote robots by interfacing the user with a robot at variable autonomy levels (Crandall and Goodrich, 2001; Sierhuis et al., 2003). These autonomy levels imply different role definitions for human and robot partners.

Although the idea of adjustable autonomy has not yet matured in the context of haptic collaboration, the notion of exchanging roles and trading control levels has emerged . Several groups examined role exchanges in human-human collaboration. Nudehi et al. (2005) developed a haptic interface for training in minimally invasive surgery. Their interface allowed to shift the "control authority" shared between two collaborating human operators, based on the difference of their actions. Reed and Peshkin (2008) examined dyadic interaction of two human operators in a 1-DoF target acquisition task and observed different specialization behaviors of partners such as accelerators and decelerators. However, they did not comment on the possible reasons or the scheduling of this specialization. Stefanov et al. (2009) proposed executor and conductor roles for human-human haptic interaction. In their framework, the conductor assumed the role of deciding on the system's immediate actions and expressing his/her intentions via haptic signals so that the executor can perform these actions. They proposed a model for role exchange using the velocity and the interaction force. This system is especially interesting in a sense that the parties are required to communicate only through the haptic channel, i.e. the conductor is assumed to express his/her intention by applying larger forces. Also in this work, they examined the phases of interaction that lead to different role distributions. In a recent paper, Groten et al. (2010) investigated the effect of haptic interaction in different shared decision situations in human-human cooperation, where an operator can choose to agree/disagree with the intention of his/her partner or to remain passive and obey his/her partner in a path following task. They observed that when operators have disagreement in their actions, the amount of physical effort is increased (interpreted as additional negotiation effort) and performance is decreased. They also found that the existence of haptic feedback further increases the physical effort but improves the performance. The findings of this study is in conflict with their previous work in (Groten et al., 2009), where haptics increased the effort but provided no performance gains. Even though they conclude that this result might stem from the fact that the former task included no negotiation, their findings are conclusory.

Even though the studies mentioned above presented very important observations regarding human-human interaction, only few groups focused on role definitions and exchange in human-robot interaction involving haptics. Evrard and Kheddar (2009) implemented a role exchange mechanism in a symmetric dyadic task where a human interacts with a robot. They defined leader and follower roles and used two functions to define each operator's control level on the task by setting certain weight parameters. Although this model ensured a systematic and smooth transition between roles, the interaction was not designed to be user-centric, and did not involve dynamic negotiation. Corteville et al. (2007) used a velocity based dominance factor to adjust the assistance level in a 1-DoF point-to-point movement task. The assistance level was set based on an estimate of the motion characteristics of the human in a known trajectory. However, the amount of assistance was predetermined and did not change dynamically during the task. Also, since they used a velocity-based dominance factor, their approach was task-dependent. Duchaine and Gosselin (2007) implemented a variable impedance control scheme for human-robot collaboration. In order to identify the parameters of this scheme, they utilized the time derivative of human force as an indicator of the human's intention of accelerating or decelerating. Passenberg et al. (2011) proposed adaptable haptic assistance in a shared control setup. They used human effort and task performance criteria to find static optimal assistance levels for certain tasks and outlined possibilities for implementing on-line adaptation. Lawitzky et al. (2010) investigated how effort sharing is achieved between a human and a robot in a table-carrying task and concluded that the cooperation quality improves with an increasing degree of robotic assistance. Wojtara et al. (2009) investigated haptic interactions between humans and robots during precise positioning of a large and long object through the decomposition of the task in the spatial domain. They assigned weights to the partners' force contribution to the task based on force cues.

Table 2.1 presents a comparison of several haptic shared control tasks implemented in recent literature. Upon close inspection of the table, we observe that about half of the tasks in question focus only on human-human interaction, while the remaining realize human-robot interaction. An immediate examination shows that in all tasks, the parties have a common goal they want to optimize, but only in two - (Groten et al., 2010) and (Oguz et al., 2012) (also see Kucukyilmaz et al. (2012))-, they have separate agendas. Also it can be seen in columns 2 and 3 that only Evrard

Table 2.1: A comparison of several shared control tasks implemented in recent literature

	Human-Robot Interaction	Simultaneous Shared Control	Sequential Shared Control	Common Goal	Separate Agendas	Separate Roles	Dynamic Role Exchange
Reed & Peshkin (2008)	×	✓	×	✓	×	✓	×
Stefanov et al. (2009)	×	✓	×	✓	×	✓	✓
Groten et al. (2010)	×	✓	×	✓	✓	✓	✓
Evrard et al. (2009)	✓	✓	✓	✓	×	✓	×
Kucukyilmaz et al. (2013)	✓	×	✓	✓	×	✓	✓
Oguz et al. (2012)	✓	✓	×	✓	✓	✓	×
Passenberg et al. (2011)	✓	✓	×	✓	×	✓	×

and Kheddar (2009) implemented a shared control scheme that is both simultaneous and sequential[1], however a dynamic role exchange between the cooperating parties has not been considered as it is done by Kucukyilmaz et al. (2013) and Oguz et al. (2010).

2.2 *Cooperative Load Sharing in Physical Human-Robot Collaboration*

The synthesis of physical robotic assistants for cooperative load sharing tasks reaches back to the early 1990's when Kosuge et al. (1993) deployed an object-centered impedance control scheme similar to that of Schneider and Cannon (1992) for a set of robots cooperating with a number of humans.

Successful hardware implementations named *MR Helper* and the distributed vari-

[1] A general categorization of shared haptic interaction, which is similar to Sheridan's classification, talks about *"simultaneous"* versus *"sequential"* haptic manipulation classes (Basdogan et al., 2000). In simultaneous haptic manipulation, both parties can actively control the task concurrently, whereas in sequential manipulation, they take turns in control.

ant *DR Helpers* (Hirata and Kosuge, 2000) encouraged a number of groups to research synthesis methods for cooperative human-robot object manipulation strategies. An overview of the achievements of Hirata and Kosuge in this field is given in (Kosuge and Hirata, 2004). The application of cooperative load transport has also been targeted by Gillespie et al. (2001) using the rather different *Cobot* approach. While Kosuge's robotic helpers could actively render a virtual object impedance behavior with features such as collision avoidance, *Cobots* cannot move on their own – they are inherently passive. However, motion induced by a human operator is projected along virtual curvatures by arranging counter-acting forces in the *Cobots*. This approach focuses on desired paths or workspace constraints rather than desired virtual dynamic object behavior, similar to the *virtual fixtures* introduced by Rosenberg (1993) as overlays such as virtual rulers guiding the operator's effector motion in telepresence setups. An approach combining desired virtual constraints and desired virtual object dynamics was proposed by Takubo et al. (2002). In their work, a robotic partner renders a virtual nonholonomic constraint – namely a virtual wheel – that prohibits sideway slipping motion and thus simplifies operation similar to a wheelbarrow. This simplification however, inhibits maneuvering of bulky objects in narrow passages. The group of Ikeura investigated the feedback behavior of a following manipulator during cooperative object transport. Human impedance characteristics were found to be the best in terms of subjective scores (Ikeura et al., 1994) and to enable natural movement profiles (Ikeura et al., 2002). All of these approaches consider robotic partners that react on user operation which certainly limits these devices' capabilities.

In order to overcome such limitations, a significant body of work was dedicated to fundamentally model human behavior in cooperative haptic tasks and to transfer findings to cooperative robotic partners. The concept of jerk minimization in human arm movements for pointing as proposed by Flash and Hogan (1985) has been transferred to cooperative manipulation by Maeda et al. (2001). This enabled a robotic partner not only to react to a human operator input but also to predict human intentions and act accordingly. Reed et al. (2005, 2006) investigated the effects of specialization in human-human interaction and successfully transferred their results to a human-robot setup so well that participants could not distinguish between the robotic partner and an actual human partner (Reed and Peshkin, 2008). Reed's findings on evolving specialization were further investigated by Groten et al. (2009) who showed that users prefer a dominance difference among collaborating partners in contrast to equally shared control. In this context, dominance refers to the actual achievement of influence or control over another and therefore reflects the individual share of the overall contribution to task success.

In order to decide on the necessary overall contribution, prior knowledge of a desired trajectory is required. Miossec and Kheddar (2008) discovered a motion model for cooperating humans that outperforms the minimum-jerk model used by Maeda et al. (2001). Based on this trajectory generation method for cooperative object moving tasks, Evrard and Kheddar (2009) developed a controller blending scheme that enables a leader/follower role allocation with one single blending parameter. Recent insights on leader/follower assignment from this group can be found in (Kheddar, 2011), which suggests that blending of stable leader and follower controllers will not necessarily result in a stable overall behavior. Human following behavior as a response to a leading robotic manipulator has been investigated in a cooperative vertical lifting task by (Parker and Croft, 2011). Behavioral hallmarks such as different frequency domains of human visual and haptic response could be discovered. An overall system architecture that comprises a confidence-based role adaptation, implemented on a very small scale humanoid robot was recently presented by Thobbi et al. (2011).

An emerging interest in intelligent physical robotic assistants in industrial settings is visible for a few years. Wojtara et al. (2009) developed a basic physical assistant for precise positioning of windshields during car manufacturing processes. Their framework proposes a strict geometrical separation of the degrees of freedom and weighs the assistant's force contribution to the task according to haptic cues.

Chapter 3

HUMAN-ROBOT COLLABORATION IN VIRTUAL WORLDS

In this chapter, we discuss our efforts to evaluate the benefits and the usability of a role exchange (RE) mechanism as a shared control scheme (also see (Oguz et al., 2010; Kucukyilmaz et al., 2011, 2012, 2013)). As a test bed, we implemented a target-hitting game, and developed a model for haptic collaboration, in which the human and the robotic agent interact through force to achieve a common goal by dynamically exchanging roles. This chapter starts with a discussion of the haptic negotiation model and its use for dynamic and natural collaborative decision making in Section 3.1. The test bed application, as it appears in (Oguz et al., 2010), is introduced in Section 3.2.

For evaluation, we establish quantitative metrics considering task performance, task kinetics and kinematics, such as completion time, path deviation, energy consumed by the partners, and work done on the manipulated object. We also suggest a metric to quantify the efficiency. Additionally, we develop subjective scales for evaluating the user-acceptability of the proposed RE mechanism (see Appendix C for more information on the scales and related questionnaires used in the human studies).

In Section 3.3, we present the results of an experimental study where the subjects are exposed to the RE mechanism without being informed about the nature of the interference they were presented with (also see (Oguz et al., 2010)). We compare the RE scheme with an equal control (EC) guidance scheme and with a condition where no guidance is present (NG). As a result of this study, we observe a clear benefit of the guidance schemes (i.e. EC and RE). Additionally, we observe that the RE mechanism presents users with an option to choose and optimize between accuracy and energy.

In Section 3.4, we discuss how knowledge about the RE mechanism affects its utility in dynamic collaboration. Within the course of an experimenal study, we explicitly guide the users on how to use the RE mechanism for completing the task. The proposed RE scheme is compared with an EC guidance method. Moreover, additional sensory cues are integrated to inform the human operator about the current role of each party during the task. We show that the RE mechanism improves task performance and the efficiency of the user as well as the joint efficiency of the partners. Furthermore, the additional sensory cues, which are used to display the control state of the collaborating parties, increase the user's awareness, perceived level of interaction, and reinforce his/her belief that the robot helps with the execution of the task (also see (Kucukyilmaz et al., 2011, 2013)).

3.1 Haptic Negotiation Model and the Role Exchange Mechanism

In this section, we describe the haptic negotiation model, which constitutes the basis of our role exchange mechanism. This model allows the interaction of two agents (e.g a human and a robotic agent) through a negotiated interface point. The haptic negotiation model is sketched in Figure 3.1. The interaction is implemented using three massless particles and a spring-damper model between them. These particles serve as the interface points, through which the parties communicate with the system. The interface points, labeled as HIP and CIP in the figure, respectively denote the human's Haptic Interface Point and the Controller's Interface Point. The operations of the parties are combined by interconnecting these two points at NIP (Negotiated Interface Point), and by allowing NIP to move the manipulated object.

This model allows the control of a virtual point to be shared between parties. It also facilitates the process of assigning different control levels (i.e. roles) to the parties. The human and the robot are granted different levels of control on the task by varying the stiffness coefficients between HIP and NIP ($K_{p,HN}$) and between CIP and NIP ($K_{p,CN}$). If $K_{p,HN}$ and $K_{p,CN}$ have equal value, the robot and the user will have equal control on the movement of the manipulated object. On the other hand, the robot will be the dominant actor if $K_{p,CN}$ has a larger value, and vice versa, the

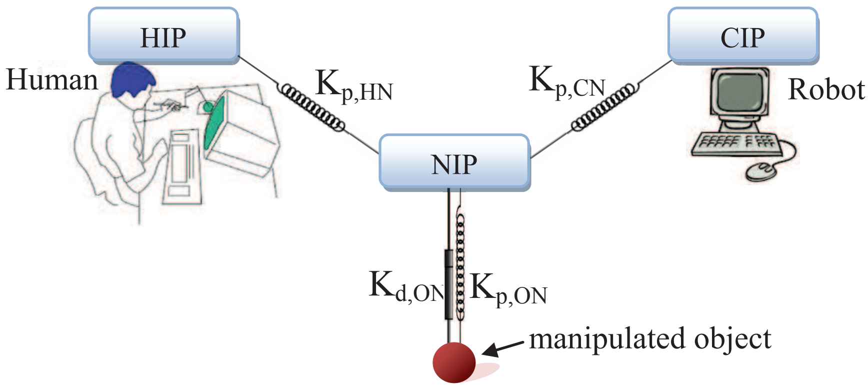


Figure 3.1: The haptic negotiation model. Force negotiation is achieved by setting the stiffness constants, $K_{p,HN}$ and $K_{p,CN}$. These constants are used to adjust the control levels of the parties.

human will be dominant if $K_{p,HN}$ is larger. $K_{p,ON}$ and $K_{d,ON}$ affect how much and how fast the object is manipulated when NIP is moved under the influence of the forces applied by the human and the robot[1].

Using the haptic negotiation model, the parties can interact through force information to exchanges roles. In our experiments, we assumed that the user would show his/her intention of taking control by applying large forces, whereas (s)he tries to relinquish control to the robot by reducing the forces (s)he applies. The robot infers the user's intention of taking control and shifts the roles as intended. In practice, the user initiates a role exchange whenever the magnitude of the force (s)he applies is above an upper threshold or below a lower threshold over a predetermined period. Note that the forces in our system vary between 0-4 N, hence the term "large force" is relative and indicates that the force applied by the user is higher than the upper force threshold. These thresholds are initially set at the beginning of the game. Depending on the implementation of the role exchange mechanism, these thresholds are either constant throughout the game (as done by Oguz et al. (2010)), or are updated with dynamically changing user-specific values (as done by Kucukyilmaz et al. (2013)).

[1]Please see Appendix A for the parameter values used in the experiments.

3.2 Haptic Board Game

We implemented an interactive game in a virtual environment in order to investigate how collaboration is affected by the inclusion of a role exchange (RE) mechanism in dynamic human-robot interaction. This game will be called the Haptic Board Game until the rest of this dissertation.

The Haptic Board Game is designed especially to create a dynamic and interactive environment that mimics a physical task, in which a human benefits from collaboration with a robot. In the game, the user controls the position of a ball with a haptic device[2] to hit cylinders on a board. The game is implemented in Microsoft Visual Studio® 9.0 using C++ with Geomagic® OpenHaptics® SDK and Open Inventor® graphics toolkit for Windows.

In the rest of this section, we describe the Haptic Board Game application in its original form as presented by Oguz et al. (2010). In particular, we explain the general design approach and the physics based model beneath the implementation.

3.2.1 Design Approach and Choice of Application

It is not easy to program robots for providing generic assistance to humans, especially in dynamic, virtual, and shared worlds. Haptic Board Game involves controlling the position of a ball on a flat board to reach arbitrarily positioned targets with the help of a haptic device. The visual representation is reflected to the user as if the ball is moved by tilting the board about the x and z axes. The goal of the game is to hit 8 randomly placed cylinders with the ball in a specific order . At the beginning of a game, all the cylinders but the target are gray, and the target cylinder is highlighted with blue. When a user hits the target, its color turns red and the new target turns blue so that users can easily keep track of the current target, as well as the previous ones throughout the game (see Figure 3.2).

[2] During the experiments, we either used a Geomagic® Phantom® Premium™ (formerly Sensable® Phantom® Premium™) or a Geomagic® Touch™ (formerly Sensable® Phantom® Omni™) device.

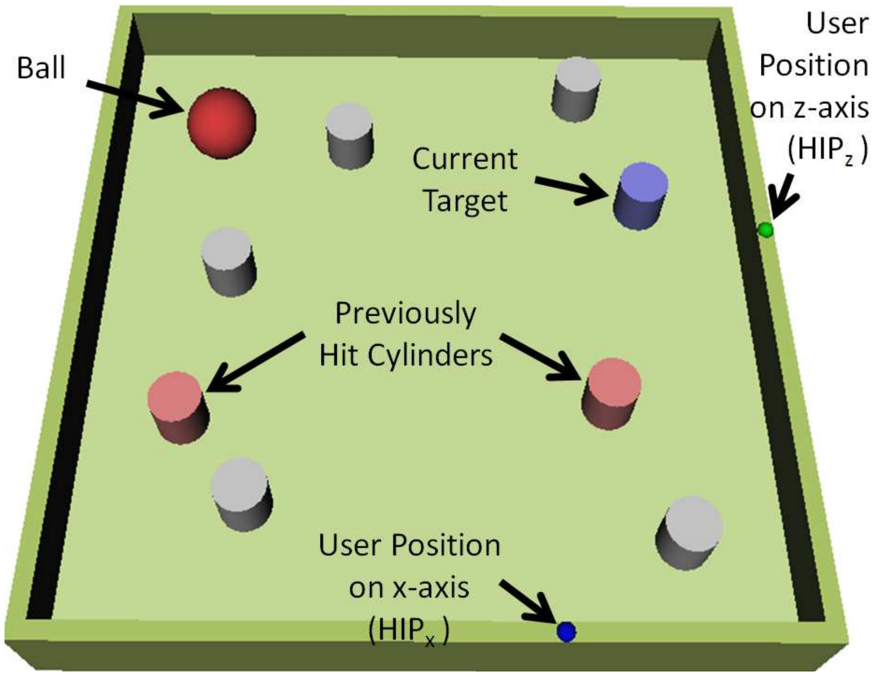


Figure 3.2: A screenshot of the Haptic Board Game. The red ball and eight randomly positioned cylindrical targets are located on a square board. The haptic device's (i.e. the user's)current position in x and z axes, are indicated respectively by the blue and the green half-spheres on the board boundaries.

Our goal is to come up with a collaboration mechanism that can improve performance under this dynamic environment in terms of time, accuracy, and efficiency of the humans while making them feel comfortable when they are working with an intelligent entity that can express intelligent reactions. Hence, we need a model that provides more than simple automated robotic guidance. To achieve this, a force-based negotiation mechanism, as explained in Section 3.1, is developed, where each party can express and sense intentions. With such an interaction oriented model, the users of the system are able to feel not only the forces generated by the inertial movements within the environment, but also those generated due to the haptic negotiation process.

3.2.2 Physics-Based Engine

The physics-based interactions used for simulating the game dynamics is shown in Figure 3.3. During the simulation, the controller moves CIP by applying a force F_C to reach a target point. This force is calculated using a PD (Proportional-Derivative) control algorithm (see appendix A for the gain values used in the experiments). Using

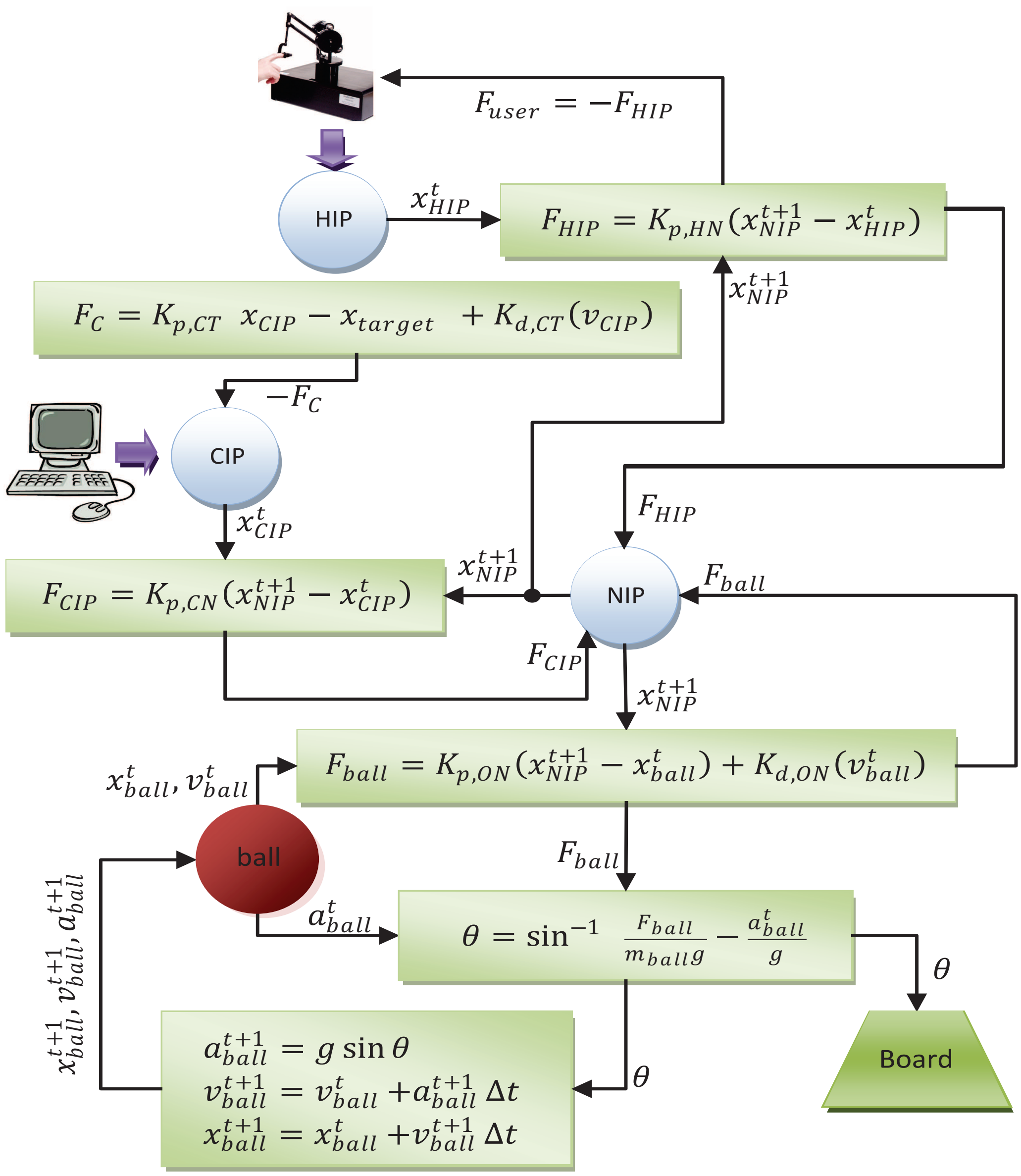


Figure 3.3: The flow of interactions within the game.

the PD controller, CIP is forced to follow a trajectory defined by the target positions that are connected to each other by line segments.

In our model, the movements of HIP and CIP affect the movements of NIP. At each time step, the new position of NIP (x_{NIP}^{t+1}) is calculated so that the system illustrated in Figure 3.1 is in static equilibrium. The new position of NIP is then used to calculate F_{CIP}, F_{HIP}, and F_{ball}. These respectively denote the forces that act on NIP by CIP, HIP, and the ball. F_{HIP} is negated and fed back to the user through the haptic device. The tilt angle of the board (θ^{t+1}) is calculated using the force acting on the ball (F_{ball}) and its acceleration (a_{ball}^{t}). Finally, the ball's new position (x_{ball}^{t+1}), velocity (v_{ball}^{t+1}), and acceleration (a_{ball}^{t+1}) are calculated and updated using Euler integration.

3.3 Experiment I

This section presents the results of the experimental study we conducted to evaluate the benefits of the suggested role exchange (RE) mechanism when the users of the system are not provided with information about the robot's behavior (also see (Oguz et al., 2010)).

3.3.1 Role Exchange Policy

As explained in Section 3.1, our system is designed to allow haptic negotiation between partners by allowing the robot to sense the human's intentions. The RE process involves dynamically changing the role, i.e. the degree of control, of the controller based on changes in human's forces.

In our implementation, we assumed that REs occur whenever the magnitude of the force that the user applies is above or below the threshold values for over 90% of a 500 milliseconds duration. In order to realize a smooth transition during REs, we defined a finite state machine (FSM) with four states as shown in Figure 3.4. Initially the system is in *Human Dominance* (S_1) state, in which the human is the actor that mainly controls the movement of the ball, while the controller only gently

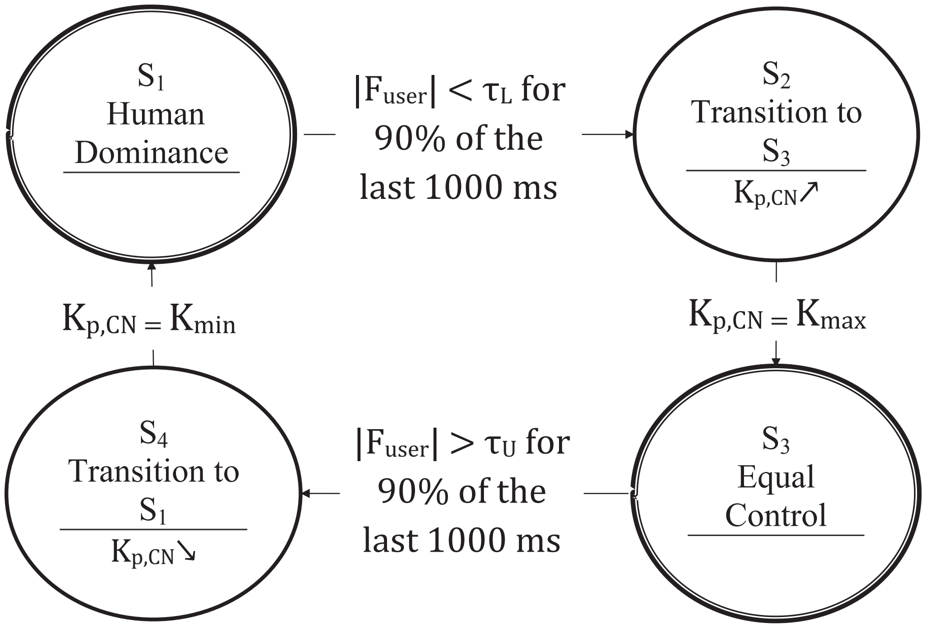


Figure 3.4: State diagram defining the role exchange policy. $|F_{user}|$ is the magnitude of the force applied by the user, τ_L and τ_U refer to the lower and upper threshold values for initiating state transitions.

assists him/her. If the force applied by the human stays below the lower threshold value for 90% of the last 500 milliseconds, then the robot assumes that the human requires more assistance. Thus, a RE occurs in favor of the robot and the system enters transition state S_2, in which the robot gradually takes control until its level of control reaches that of the human's. The system stays in S_2 for a period of 1000 milliseconds[3], where $K_{p,CN}$ is gradually increased to transfer control to the robot. After this period is over, the system enters the *Equal Control* (S_3) state, where the the robot's and the human's control levels are equal. Clearly, at this stage, a series of state transitions may occur from S_3 towards S_1 over transition state S_4 if the robot captures the user's desire to take over control. In this case, the robot releases control by decreasing $K_{p,CN}$ over a period of 1000 milliseconds and the human becomes the

[3]The transition interval was selected to be larger than the typical motor response time (reaction time + movement time) of a human operator in reaching tasks ($\approx$ 400 ms)

dominant actor of the system. Note that during state transtions (i.e. in states S_2 and S_4), the stiffness coefficient $K_{p,CN}$ is varied linearly over time to let the robot change its control level.

During preliminary studies, we noticed that the force profiles of users on x and z axes do not necessarily display similar patterns. For instance, a user can prefer to be attentive to the movement only in one axis and try to align the ball on that axis first, only then to switch his/her attention to the movement on the other axis. This may be due to the positioning of the target cylinders: Some consecutive targets were positioned diagonally, whereas some were in parallel to each other on one axis. Another possible reason can be that the users might not feel comfortable controlling the ball diagonally and prefer a sequential control on axes. Hence, we extended our role exchange method to allow state transitions to occur on each axis separately. In other words, the robot can provide full guidance on one axis whereas it just remains *recessive* on the other, letting the user remain the *dominant* actor on that axis.

An example of such state transitions can be seen in Figure 3.5. For example, at the fifth second, based on the force input in the x-axis, a transition occurs from *Human Dominance* (S_1) state to transition state (S_2), i.e the controller starts to get more control on the x-axis. About one-half of a second later, a similar state transition occurs from *Human Dominance* state to a transition state (S_2) on z-axis. Spending one second on the transition state, another transition toward *Equal Control* (S_3) state takes place, first for x-axis then for z-axis. At around sixth second of playing, controller becomes as effective as the user for controlling the ball, hence the condition becomes identical to EC.

3.3.2 Experiment

This section presents the experimental conditions, design, and the procedure as well as the measures used in the analyses.

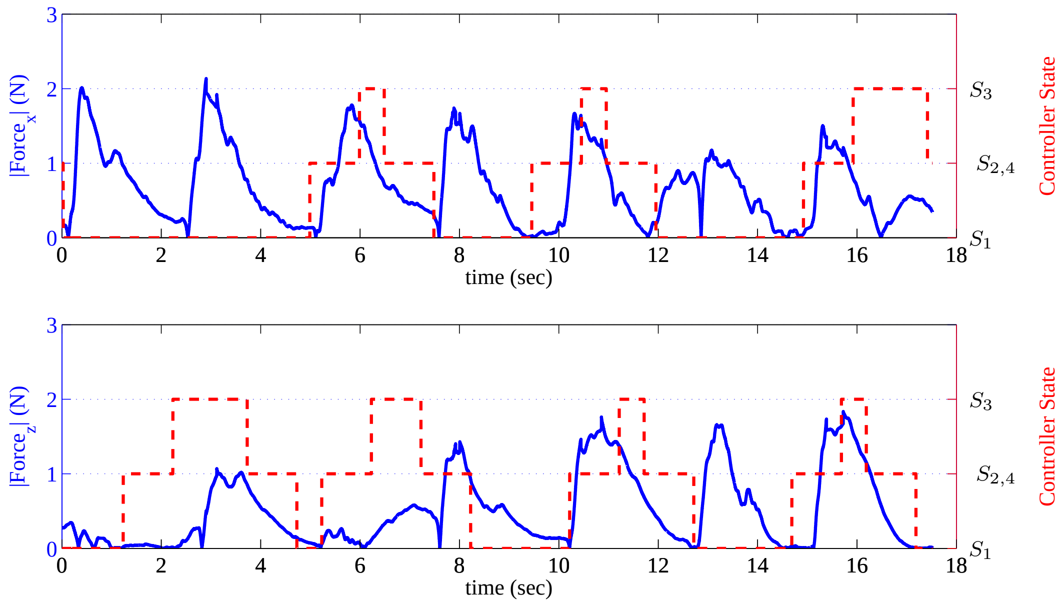


Figure 3.5: A sample trial for the RE condition. Blue lines denote the user's force profile in each axis, whereas the red square waveform drawn in dashed lines indicate the state of the system, which reads the current role of the controller in the related axis on the right hand sides of the plots. The upper and lower plots represent the information in x and z axes respectively. (S_1: Human Dominance state, $S_{2,4}$: transition states, S_3: Equal Control state. Note that for the sake of simplicity, transition states S_2 and S_4 are merged and labeled as $S_{2,4}$.)

Conditions

No Guidance (NG): The user plays the game without robotic assistance. CIP is clamped to NIP to prevent any intervention ($K_{p,HN} = 0.09$ N/m and $K_{p,CN} = 0$ N/m). The user feels spring-like resistive forces due to the rotation of the board, but no haptic guidance is given to control the ball position on the board.

Equal Control (EC) The user and the robot share control equally at all times to move the ball. This is achieved by choosing $K_{p,HN}$ and $K_{p,CN}$ constant and equal to each other ($K_{p,HN} = K_{p,CN} = 0.09\ N/m$). In this condition, the user feels guidance forces applied by the controller as well as forces generated due to the dynamics of the game.

Role Exchange (RE) The robot negotiates with the user to decide on how they should share control based on the user's force profile. The robot's control level can be either equal to that of the user's or smaller for each DoF. When partners share control equally in both DoFs, this condition becomes identical to EC. On the other hand, when the robot switches to a rather loose control level, the user becomes *dominant* on controlling the ball and the robot becomes the *recessive* partner. In between these states, robot's control is blended from equal to human dominance or vice versa by dynamically varying the $K_{p,CN}$ value between 0.03 N/m and 0.09 N/m as explained in Section 3.3.1.

Procedure and Participants

10 subjects (5 female and 5 male) participated in our study. Since none of the subjects were familiar with a haptic device, we introduced the haptic device to each subject verbally and through the use of certain training applications irrelevant to the board game. Each subject utilized these applications for about 15 minutes until (s)he felt comfortable with the haptic device. The experiment consisted of three sessions, each of which took about half an hour. In each session, the subjects played under either no guidance (NG), equal control (EC), or role exchange (RE) condition. In order to eliminate learning effects on successive trials, the order of experimental conditions was mixed, with at least three days between two successive sessions. We paid attention to provide the same physical setting for all sessions, such as the positioning of the haptic device, the robot, and the subjects' seats. Subjects were instructed to grasp the stylus in the most effective and comfortable way possible. During the sessions, the full system state (i.e. positions of HIP, CIP, NIP, and ball; all the individual forces of each spring/spring-damper system, etc.) was recorded at 1 kHz.

In NG and EC conditions, each subject played the haptic board game 15 times for a single session. As explained earlier in Section 3.2, a single game consists of hitting eight randomly placed cylinders in a specific order, by controlling the ball. When a game is completed, all the cylinders turn gray again, and another game starts without interrupting the system's simulation. To avoid possible fatigue, subjects took a break after the 5^{th} and the 10^{th} games.

Under RE condition, the subjects played an additional game at the beginning of each block of 5 games for the purpose of determining the thresholds, so a total of 18 games were played by each subject. During these extra games, subjects played under NG. In order to determine the force thresholds, we recorded the subject's force profile during these initial trials, then took the average and the standard deviation of the subject's forces, so that the lower and upper threshold values for the next 5 games can be determined by

$$\tau_L = \mu_F - \sigma_F,$$

$$\tau_U = \mu_F + \sigma_F,$$

where μ_F and σ_F are respectively the average of the forces applied by the subject during the initial game and the standard deviation of these forces.

3.3.3 Measures

This section introduces the quantitative and subjective measures used in the evaluation.

Subjective Measures

After each experiment, the subjects were given a questionnaire, the questions of which can be found under Appendix C.1. As mentioned before, the subjects neither had information about the different conditions we were testing, nor knew whether they took these experiments with different conditions or not.

For the questionnaire design, we adopted the technique that Basdogan et al. (2000) used previously in shared visual environments. A total of 18 questions were answered by the subjects. Eight of the questions were about personal and demographic information, one was reserved for users' feedback, and the remaining nine were about variables directly related to our investigation. Some of the questions were paraphrased, and asked again, but scattered randomly in the questionnaire (see Appendix C.1). For evaluation, the averages of these questions, that fall into the same category, were calculated. Questions were asked in five categories:

1. *Performance:* Each subject was asked to assess his/her performance by rating himself/herself on a 5-point Likert scale.

2. *Humanlikeness:* Two questions using a 7-point Likert scale asked the subjects whether the control felt through the device, if any, was humanlike or not.

3. *Collaboration:* Two questions using a 7-point Likert scale asked the subjects whether they had a sense of collaborating with the robot or not. Two more questions were asked to determine whether the control made it harder for the subjects to complete the task or not. Answers to these 4 questions were evaluated using a 7-point Likert scale.

4. *Degree of User Control:* A single question using a 7-point Likert scale asked the subjects about the perceived degree of their control on the task.

5. *Degree of Robot Control:* A single question using a 7-point Likert scale asked the subjects about the perceived degree of robot's control on the task.

Quantitative Measures

We quantified user performance in terms of task completion time, total path length during the game, deviation of the ball from the ideal path and integral of time and absolute magnitude of error (ITAE).

Task performance The completion time of each game is recorded to measure task performance.

Path length Total path length of the ball is computed at the end of each game.

Path deviation For the board game, we defined the ideal path between two targets to be the straight line segment connecting the centers of the targets. Hence, between two targets, the deviation is defined to be the area of the region formed between the ideal path connecting consecutive targets and the actual path of the ball. Total deviation in a single game is calculated by summing the deviations between consecutive targets throughout the course of the game.

Integral of time and absolute magnitude of error (ITAE) ITAE criterion is defined as:

$$ITAE = \sum_{i=1}^{7} \left(\int_{t=T_i}^{T_{i+1}} t\,|e(t)|\,dt \right).$$

Note that we calculate ITAE for consecutive target pairs and sum these to get the ITAE of a game. Here, time T_i is taken to be the moment when the ball reaches i^{th} target. Error $e(t)$ is the deviation of the ball from the ideal path (i.e. the length of the shortest line segment connecting the ideal path and the ball's actual position) at time t during the game. The ITAE criterion has the advantage of penalizing the errors that are made later. In other words, it is used to punish the users more severely if they deviate from the path when the ball gets close to hitting the target.

Work done on the ball We examined the work done on the ball by the user. The spring located between NIP and HIP acts as the bridge between the system and the haptic device and any force exerted by it is sent directly to the user. Hence, this force acts as the force felt by the user. The work done by the spring is basically calculated by

$$W = \int_{t=0}^{T} \frac{1}{2} K_{p,HN}\ x(t)^2,$$

where T is the completion time of the game, $K_{p,HN}$ is the stiffness constant of the spring, and $x(t)$ is the extension of the spring at time t.

3.3.4 Results

This section presents the subjective and quantitative results of the the experimental study we conducted. Statistically significant differences between conditions are investigated through paired t-tests.

Subjective Evaluation

The questionnaire presented in Appendix C.1 is designed to measure the self-perception of users' performance, the humanlikeness and the collaborative aspects of the system, as well as the degree to which the users feel they and the robot has control over the task. Note that the results presented in this section are gathered using the responses of 9 subjects out of 10. After an initial analysis, we found that one subject did not report any sensation of robot control in the questionnaire, therefore the questions, which were about the nature of robot control, were rendered inapplicable. Hence, his/her responses were excluded from further analysis.

The subjective evaluation results shown in Figure 3.6 imply a higher sense of collaboration for the role exchange (RE) and equal control (EC) conditions ($p < 0.01$) when compared to the no guidance (NG) condition. There is no significant difference between the perceived degree of collaboration felt under EC and RE conditions.

Figure 3.7 presents the subjective evaluation results on the self-perception of user performance. The subjects believe that they perform better under EC and RE conditions than they do under NG condition. We discovered statistically significant differences between EC and NG (*p-value*< 0.005) and RE and NG (*p-value*< 0.05). Again, there is no significant difference between the EC and RE. Subjects claim that

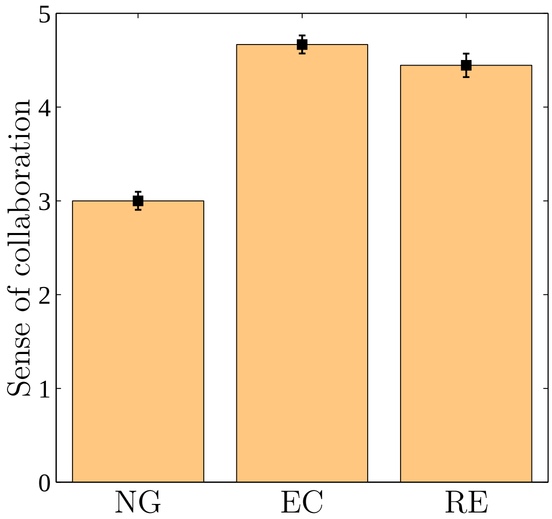


Figure 3.6: Means of the subjects' responses to questions regarding the amount of collaboration during the task and the standard error of the means (NG: No Guidance, EC: Equal Control, RE: Role Exchange)

they perceive a similar level of control throughout the game in all three conditions. On the other hand, they also feel no difference between the level of robot control on different conditions. However, based on the averages of the responses to the control questions, we observe that the subjects' feeling of being in control and their perception of robot's involvement get closer to each other in RE condition, as illustrated in Figure 3.8. Even though the subjects perceive reduced control over the game, they have a stronger sense of participation from the robot. This may also be a sign of the subjects' increased perception of collaboration under RE.

Finally, no significant difference is observed between EC and RE conditions in terms of the humanlikeness of the robot (see Figure 3.9). On the other hand, subjects feel that under RE, the robot's negotiation strategy is more humanlike compared to NG (p-$value$ < 0.05). Our negotiation model allows role exchange and provides the controller with the ability to take over/release the control of the game.

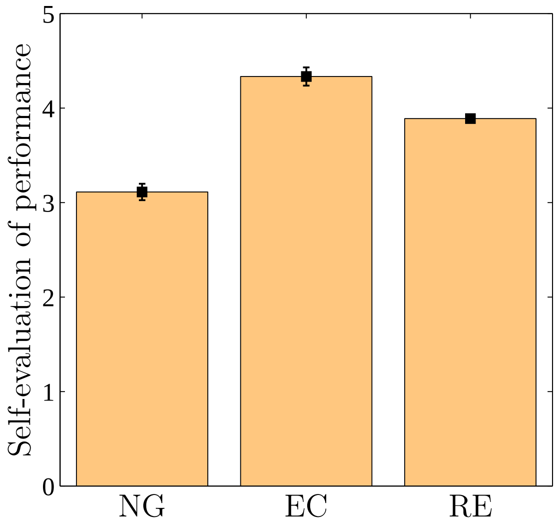


Figure 3.7: Means of the subjects' responses to questions regarding self evaluation of how well they performed the task and the standard error of the means (NG: No Guidance, EC: Equal Control, RE: Role Exchange)

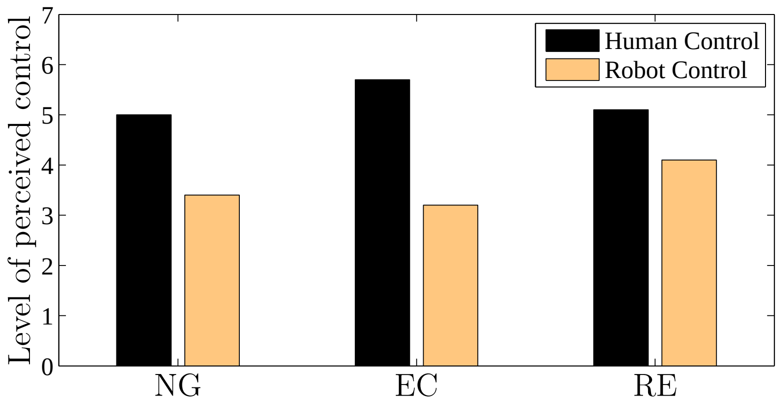


Figure 3.8: Mean responses to questions regarding how much the subjects felt in control, and how much they felt the robot was in control for each condition with SEM error bars. *Human Control* and *Robot Control* respectively represent the control level of the user and the robotic agent.

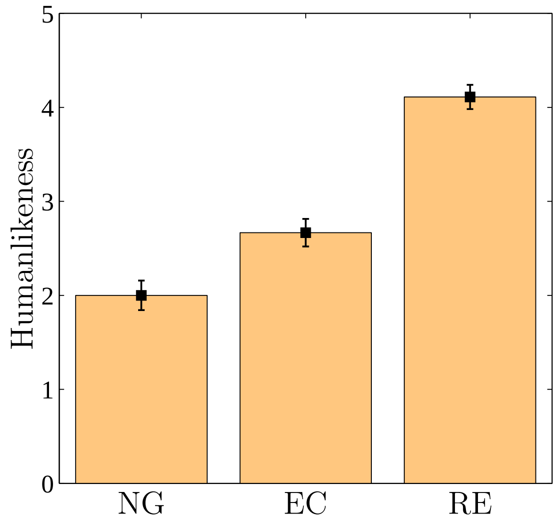


Figure 3.9: Means of the subjects' responses to questions regarding the humanlikeness of the robot and the standard error of the means (NG: No Guidance, EC: Equal Control, RE: Role Exchange)

Quantitative Measurements

In order to investigate spatial and temporal task performance, we computed the average completion times, total path lengths, deviations from the ideal path, and ITAEs of each condition.

Upon closer inspection of Figure 3.10, we observe that for all performance parameters, the paired differences between conditions follow a similar trend: The best task performance is observed with a static equal control guidance scheme (EC), while the worst performance is realized when no guidance is given (NG). On the other hand, the performance of the role exchange (RE) condition falls in between the two. According to paired t-test results, we discovered statistically significant differences between all three condition pairs (p-$value = 0.05$).

Figure 3.11 illustrates the the average work done by the user on the ball, which is a measure of energy consumed by the human. Even though the spatial and temporal

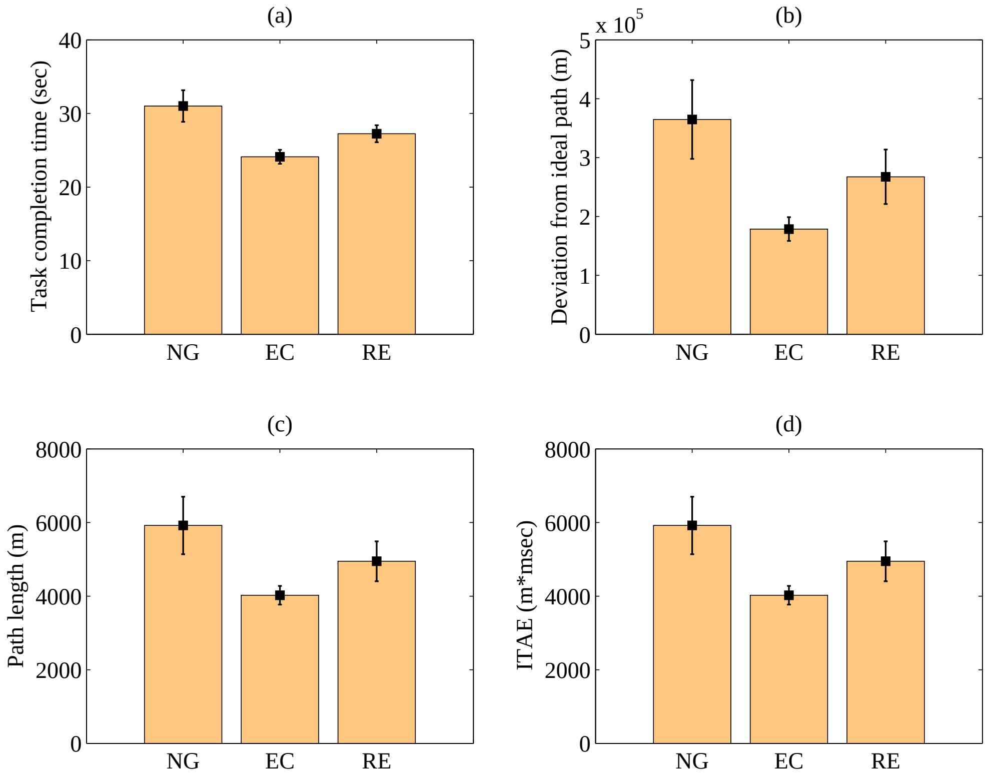


Figure 3.10: Means of (a) completion times, (b) path deviations, (c) path lengths, and (d) ITAEs per condition and standard errors of the means (NG: No Guidance, EC: Equal Control, RE: Role Exchange)

task performance is inferior in NG and RE conditions compared to the EC condition, the subjects spend less energy under these conditions. Paired t-test results on the average work done by the human do not indicate a statistically significant difference between NG and RE conditions, whereas both are lower than the both axes guidance condition ($p < 0.05$). As these results indicate, RE has higher energy requirements, while NG has inferior completion time and spatial error properties. Hence, the role exchange mechanism allows us to trade off accuracy for energy without causing user dissatisfaction.

We also examined the role exchange trends of subjects. As seen in Figures 3.12

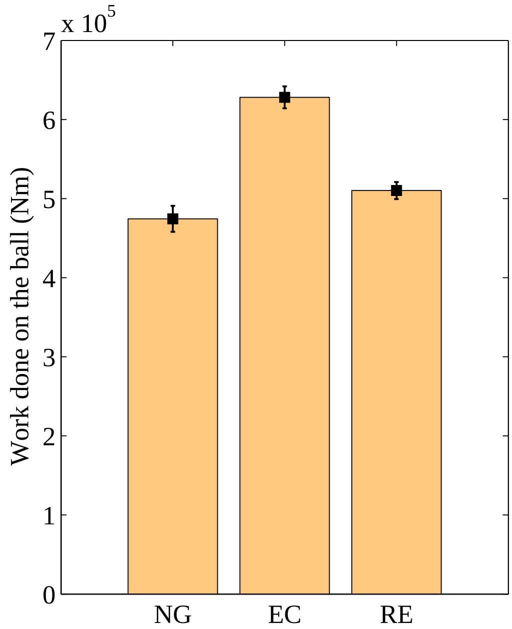


Figure 3.11: User averages of energy on the spring between NIP and HIP and standard errors of the means (NG: No Guidance, EC: Equal Control, RE: Role Exchange)

and 3.13, the results show that the average number of state transitions as well as the average time that the controller stays at a given state varies from subject to subject. This is a sign of the existence of user preferences during game play. Even though subjective evaluations suggest that the development of these preferences is subconscious, this is a strong indication that our role exchange mechanism provides a more personal experience compared to classical guidance mechanisms.

3.4 Experiment II

This section presents the results of the experimental study we conducted to evaluate the benefits of the suggested role exchange (RE) mechanism when the sers of the system are not provided with information about the robot's behavior (also see (Kucukyilmaz et al., 2011, 2012, 2013)).

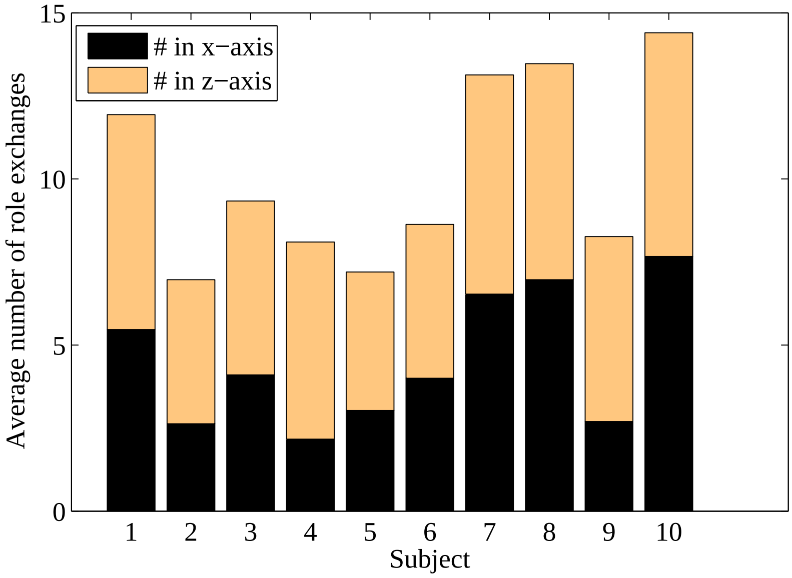


Figure 3.12: Average number of role exchanges performed by each subject over 15 games. Each subject ends up with a different number of role exchanges, indicating that they adopt certain strategies during the course of the game.

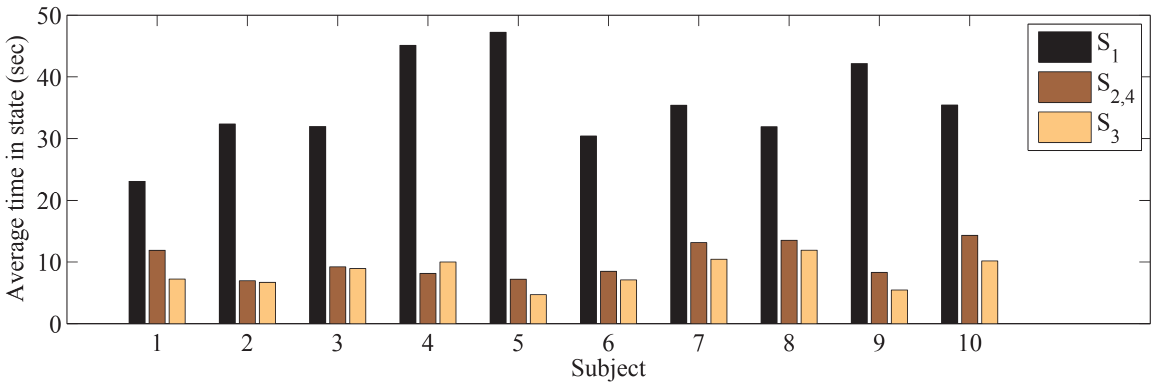


Figure 3.13: Average time spent by subjects in each controller state. S_1, $S_{2,4}$, and S_3 respectively represent *Human Dominance*, *Transition*, and *Equal Control* states, as depicted in Figure 3.4. Note that for the sake of simplicity, transition states S_2 and S_4 are merged and labeled as $S_{2,4}$.

3.4.1 Role Exchange Policy

As mentioned in Section 3.1, the user initiates a role exchange whenever the magnitude of the force (s)he applies is above an upper threshold or below a lower threshold over a predetermined period. Upper and lower force thresholds are initially set at the beginning of the game and updated by adaptively changing user-specific values (as done by Kucukyilmaz et al. (2013)):

$$\tau_L = \mu_F - \sigma_F,$$

$$\tau_U = \mu_F + \sigma_F,$$

where μ_F and σ_F are respectively the average of the forces applied by the user and the standard deviation of these forces.

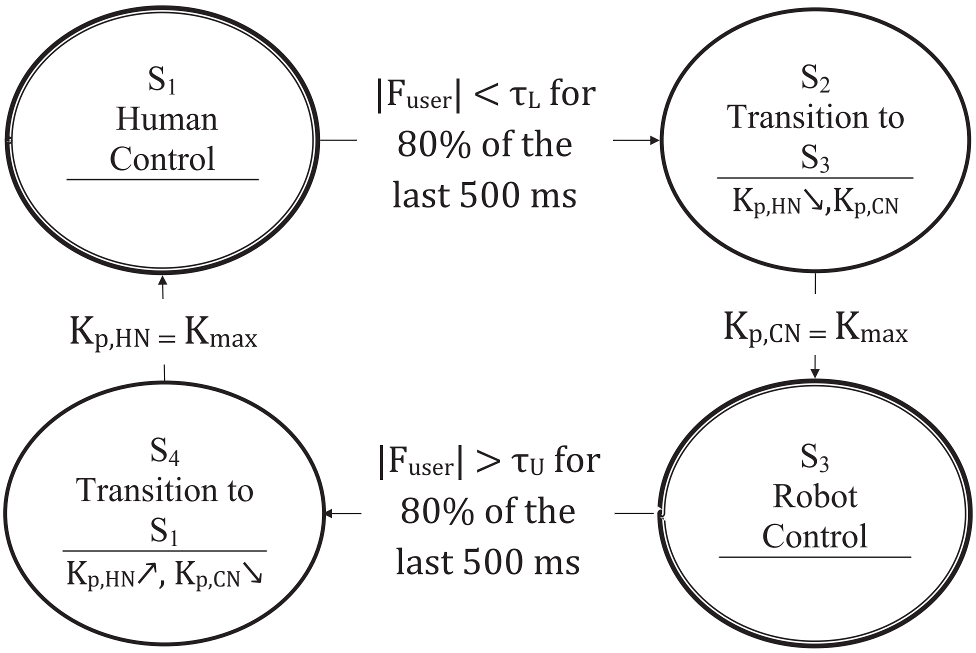


Figure 3.14: State diagram defining the role exchange policy. $|F_{user}|$ is the magnitude of the force applied by the user, τ_L and τ_U refer to the lower and upper threshold values for initiating state transitions.

Figure 3.14 illustrates the finite state machine (FSM) used to realize a smooth transition during REs. The states of the FSM define the interaction states within the system. *Human Control* (S_1) and *Robot Control* (S_3) states express the two extreme control levels that are defined in our application. Initially the system is in S_1, in which the user acts as the controller of the task. If the user wants to, (s)he can give control to the robot. We designed the role exchange mechanism so that the forces applied by the user need to stay below the personalized lower threshold value for more than 80% of a 500 millisecond duration to initiate a role exchange. Hereby, the user will make the system enter transition state S_2, in which the control is gradually shifted to the robot until the predefined control transition period is over (i.e. 750 ms)[4]; only then the system enters *Robot Control* state (S_3). Similarly, when the system is in *Robot Control* state (S_3), the user can decide to take over control by exerting forces larger than the upper threshold. Then, a series of state transitions will occur from S_3 to transition state S_4, and then to *Human Control* state (S_1) in succession. In transition states (S_2 and S_4), the stiffness coefficients are varied linearly over time to let the user and the robot share control in variable degrees.

3.4.2 Modifications to the Haptic Board Game

We modified the haptic board game in order to increase the utility of the role exchange mechanism. We tried to make the Haptic Board Game more difficult, so that the users are further motivated to demand robotic guidance. Figure 3.15 illustrates the new layout of the Haptic Board Game. In the previous setup, the game was fast, and because of this, even the small mistakes that the user made created huge temporal and spatial errors. According to Fitts' Law, the time to acquire a target increases with the distance to the target and as the size of the target decreases (Fitts, 1992). Hence, we enlarged the board and scaled down the sizes of the targets (see Appendix A).

During the game, instead of just hitting targets with the ball, the user is asked to

[4]The transition interval was selected to be larger than the typical motor response time (reaction time + movement time) of a human operator in reaching tasks ($\approx$ 400 ms) to ensure smooth transitions (Kelso, 1982).

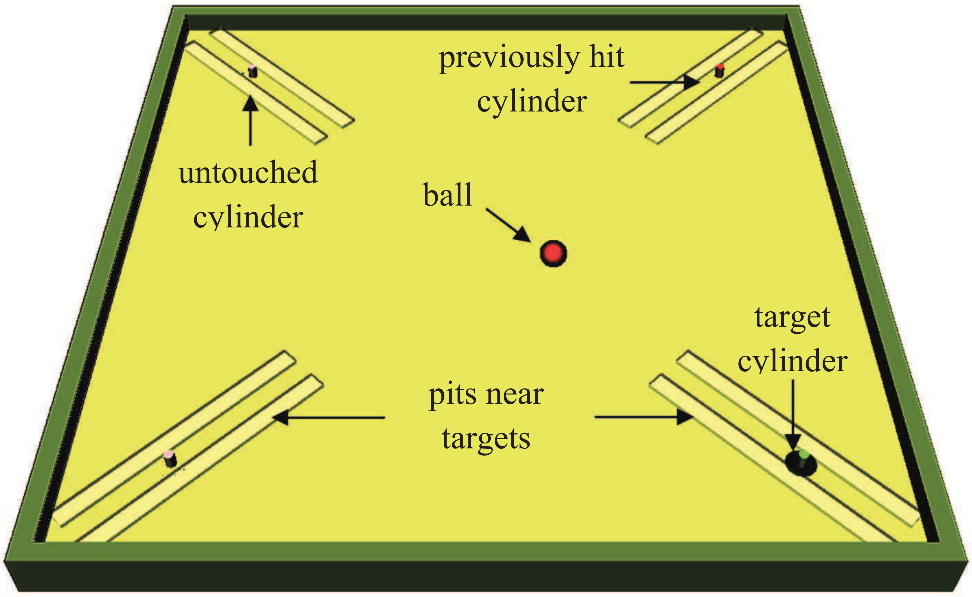


Figure 3.15: A screenshot of the haptic board game.

move the ball to hit the target cylinder and wait on it to the count of 10. A counter appears in the middle of the screen to alert the user to the countdown status while the ball resides on the target cylinder. If the user succeeds in staying on the target until the end of the countdown, the color of that cylinder changes to bright red, indicating that it has been collected, and a new target cylinder is determined. This cylinder is colored green to indicate that it is the new target cylinder the user should hit. In Figure 3.15, the cylinder in the upper right corner of the board was previously hit, whereas the target cylinder lies at the lower right corner. The remaining two cylinders are unhit. To motivate the users, we display a set of messages on the screen at the end of a trial -after hitting all 4 cylinders on the board. These messages bear either positive (i.e. “Good job”, “Much better”, “Excellent”) or negative (i.e. “You can do better”) meaning and are invoked regarding the improvement or deterioration in the user’s performance.

To further complicate the game, each cylinder is located in between two pits which diagonally extend towards the center of the board. The users are instructed to avoid falling into these pits. If the ball falls in a pit, that pit is highlighted to warn the user (Figure 3.16) and the ball is imprisoned in the pit. To leave the pit, the user should move the ball towards the entrance of the pit. As an additional penalty, if the ball falls in a pit, all acquired targets are undone, hence the trial is restarted. The pits are designed to serve as "difficult" regions for the human, where the user is anticipated to ask for robotic guidance. It is relatively "easy" to control the movements of the ball outside the pits. This design is chosen to create a task where a human and a robot can perform better than one another at different times during the execution of the task. Again, as a result of the movement of the ball, the board is tilted about x and z axes and the users are fed back with forces due to the rotation of the board.

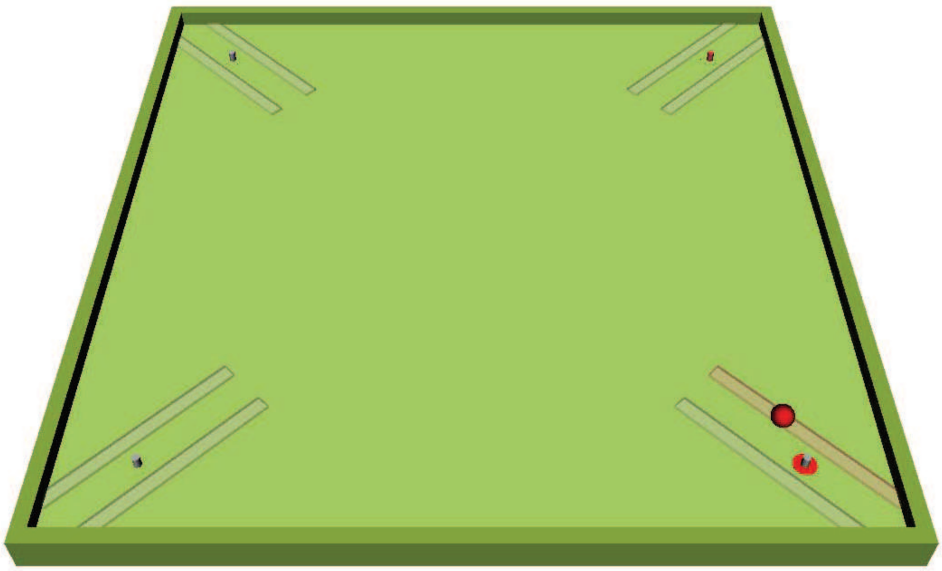


Figure 3.16: A screenshot of the haptic board game with the ball fallen into a pit.

In order to implement robotic guidance within the pit areas, three via points are defined for each target as illustrated in Figure 3.17. The first via point is used to move CIP to the entrance of the pit. Upon reaching the first via point, the ball is guided by CIP to the target cylinder between the pits with the help of the second via point. Finally, for exiting the pit, CIP leads the ball out of the pit through the use of the third via point.

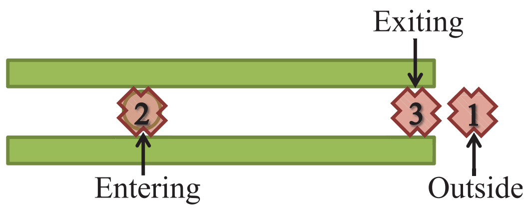


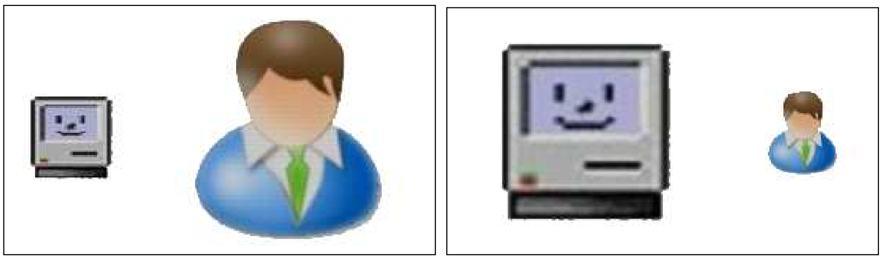
Figure 3.17: Three via points are used by the robot to define the desired trajectory of the ball: at the entrance of the pit (1), on the target (2), and at the exit of the pit (3).

3.4.3 Additional Sensory Elements

An advantage of our collaborative model is that it allows the integration of different sensory cues to display the control state. As explained in Section 3.3, we observed that when the users are not informed on the nature of the task, some of them fail to understand that their control level within the task is changing. Hence, for this study, we aimed to make the underlying mechanism as visible as possible through the integration of visual and vibrotactile informative cues.

Visual Cues

Our application requires users to attend to visual information in order to successfully complete the game. We used two role indication icons, which are displayed over the board to display the control levels of the parties (see Figure 3.18). For instance, in Figure 3.18(a) , the icon for the human (on the right) has greater size, indicating the dominance of the user. Similarly, in Figure 3.18(b), the robot's icon (on the left) is larger, indicating that the robot has taken control of the game. The sizes of the icons serve as metaphors for the parties' control levels. The icons are enlarged and shrunk gradually based on the transition process discussed in Section 3.1 to demonstrate the smooth transition between control levels (i.e. roles). We initially considered locating two role indication bars at each side of the board or a single one on top, which would illustrate the parties' control levels. However, these were not successful in attracting the users' attention. Hence, we selected the icons in Figure 3.18 for role-indication.



(a) Human Control (b) Robot Control

Figure 3.18: Two configurations for the role-indication icons.

Vibrotactile Cues

In our application, the users rely on force feedback to choose their control actions over the ball movements. Moreover, all negotiation is done through force information. In order to signal the active state of interaction, we used the same channel to display vibrotactile cues to the users. These cues are implemented as vibrations in the y-direction, hence don't interfere with the movement of the ball in any way. Two different types of cues are implemented:

Buzzing is a high frequency vibration (100 Hz) presented to the user through the haptic device during state S_2. It signals the initiation and occurrence of role exchange.

Tremor is defined as an involuntary shaking of some body part (i.e. trembling). In order to signal the presence of robot control in state S_3, a low frequency vibration varying between 8 and 12 Hz is artificially generated and continuously displayed to the user while the system is in this state.

The choice of the displayed cues and the way they are displayed are not arbitrary. In small-scale pilot studies, we investigated the effectiveness of different cues displayed by different sensory modalities (i.e. vision, sound, and haptics) to convey the control state to the user. However, only the visual and vibrotactile cues in their current forms were found to be effective. In the end, we have chosen to present visual and vibrotactile cues simultaneously to make information processing easier through the acquisition of the same information through multiple channels (Wickens et al., 1997).

3.4.4 Experiment

This section presents the experimental conditions, design, and the procedure as well as the measures used in the analyses.

Conditions

Equal Control (EC) The user and the robot share control equally at all times to move the ball. This is achieved by choosing $K_{p,HN}$ and $K_{p,CN}$ constant and equal to each other ($K_{p,HN} = K_{p,CN} = 0.25N/m$). In this condition, the user feels guidance forces applied by the controller as well as forces generated due to the dynamics of the game.

Role Exchange (RE) At any point during the game, the user can hand/take over the control of the ball to/from the robot by altering the forces (s)he applies through the haptic device. The robot infers the user's intention of taking over or giving up the control of the game based on the user's force profile and updates its degree of control on the ball[5].

VisuoHaptic Cues (VHC) As in RE condition, the user can initiate role exchanges to get the robot to dynamically change its degree of control on the ball. Additionally, role-indication icons, buzzing, and tremor are displayed to inform the user about the state of the system.

[5] The stiffness coefficients $K_{p,HN}$ and $K_{p,CN}$ are dynamically varied under RE and VHC ($0.05N/m \leq K_{p,HN} \leq 0.45N/m$ and $K_{p,CN} = 0.5N/m - K_{p,HN}$)

Procedure and Participants

30 subjects (9 female and 21 male), aged between 21 and 28, participated in our study. All of the subjects were right handed, and they interacted with a Geomagic® Phantom® Premium™ (formerly Sensable® Phantom® Premium™) haptic device using a thimble attachment. We conducted a within subjects experiment, in which each subject experimented with all three conditions in a single day. A practice condition, under which the user plays the game without robotic assistance, was initially presented to each subject to familiarize him/her with the system. The guidance conditions (EC, RE, and VHC) were then presented to the subjects in permuted order to balance learning effects. 5 subjects were tested in each of the six permutations of all three guidance conditions. The subjects were given detailed instructions about the conditions. However, since the conditions were presented in mixed order, in order to avoid any perceptual biases, the guidance conditions were labeled as “Game A”, “Game B”, and “Game C”, whereas the practice condition was labeled as the “Practice Game”.

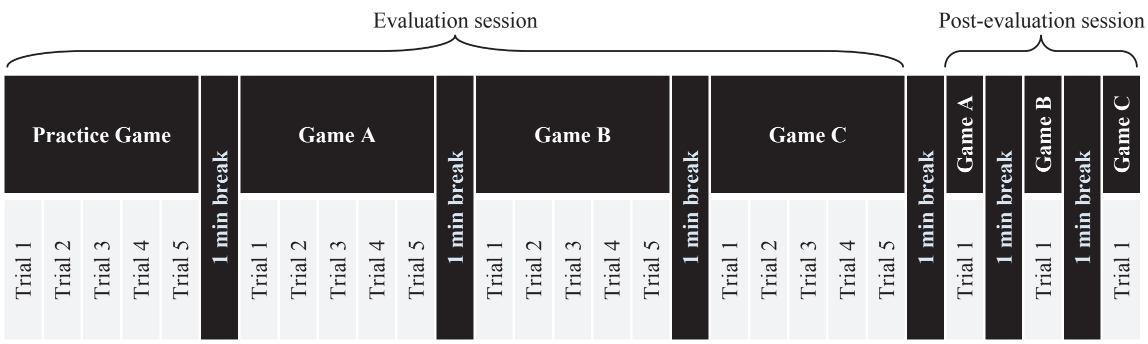


Figure 3.19: The order of the conditions displayed to the subjects in the experiment (Practice Game: no assistance; Game A/B/C: one of EC, RE or VHC in permuted order)

The experiment consisted of an evaluation and a post-evaluation session as detailed in Figure 3.19. During the evaluation session, the subjects played the haptic board game 5 times (i.e. 5 trials) under each condition. The subjects first played the game without robotic guidance, afterwards they played the game under one of the guidance conditions in mixed order. The trial number was displayed in the upper right corner of the game screen. When a trial was over, another trial was started automatically without any interruption until all 5 trials were completed. In each trial, the order of the target cylinders was modified in a controlled manner so that the subjects do not memorize a specific motion path. After playing the game successfully under the same guidance condition for 5 times, a 1-minute break was given to the subjects and a new game was started in a different guidance condition. Once the subjects finished the evaluation session, they were given another break before starting the post-evaluation session. In this session, the subjects played the game only once (i.e. one trial only) under each guidance condition in succession (Games A, B, and C) to remember the conditions and compare the differences in their experiences.

3.4.5 Measures

This section introduces the quantitative and subjective metrics used in the evaluation.

Quantitative Measures

For quantitative analysis, we utilized the data collected during the evaluation session.

We quantify task performance in terms of task completion time and the number of faults made by the user (i.e. how many times a user falls into a pit) in each trial. We also examine the energy consumed by the partners as an indication of physical effort, and the work done to move the ball in order to complete the task (each are normalized with respect to task completion time). Using these two measures, we also introduce an efficiency measure.

Task performance: The completion time of each trial and the total number of faults are counted as performance measures.

Consumed energy (E): Assuming that no energy is stored in the springs at the beginning, the energy consumed by the human partner is calculated by the dot product of the displacement of HIP and the force exerted by the spring located between NIP and HIP as:

$$E_H = \int_{P_H} |F_{HIP} \cdot dx_{HIP}| \,,$$

where P_H is the path traversed by HIP during the trial. Similarly, the energy consumed by the robot (i.e. the controller) is computed as:

$$E_C = \int_{P_C} |F_{CIP} \cdot dx_{CIP}| \,,$$

where P_C is the path traversed by CIP during the trial.

Work done on the ball (W): The work done on the ball is computed regarding the displacement of the ball and the force acting on the ball by the human and the robot (i.e. the controller):

$$W_H = \int_{P_B} |F_{HIP} \cdot dx_{ball}| \,,$$

$$W_C = \int_{P_B} |F_{CIP} \cdot dx_{ball}| \,,$$

where P_B is the path traversed by the ball during the trial. The total work done on the ball by the partners is computed as:

$$W_{Total} = \int_{P_B} |(F_{HIP} + F_{CIP}) \cdot dx_{ball}| \,.$$

Efficiency (η): Efficiency, in its broad sense defines the ability to produce the desired output with minimum expenditure of time or effort. Groten et al. (2009) proposed an efficiency measure for human-robot interaction, which related energy and task performance. On the other hand, our efficiency metric takes the performed work and the energy consumption into account; hence it establishes a well defined way of measuring the mechanical efficiency in a physical task. We define efficiency as the work done on the ball divided by the consumed energy:

$$\eta = \frac{work\ done\ on\ the\ ball}{consumed\ energy}.$$

It should be noted that the individual efficiencies of the partners are independent of the stiffness and the damping coefficients used for the haptic negotiation model, hence it enables us to compare different guidance conditions. Upon closer inspection, we see that the human partner can maximize his/her individual efficiency, $\eta_H = \frac{W_H}{E_H}$, if (s)he does a large amount of work on the ball with a small effort. However, the joint efficiency of the dyad, $\eta_{Total} = \frac{W_{Total}}{E_{Total}}$, is mostly affected by the harmony of the collaborating partners. If, for example, the human partner continuously acts against the will of the robot, both parties will spend significant effort, yet will fail to move the ball. In such a case, even though the effort is high, the work done on the ball will be small; hence the joint efficiency will be low for the dyad.

Subjective Measures

After experimenting with each condition, the subjects are given a questionnaire (see Appendix C.2), which is designed with the technique Basdogan et al. (2000) have used in the past for investigating haptic collaboration in shared virtual environments. The questionnaire asks users to comment on their experiences under the 3 guidance conditions (EC, RE, and VHC). Some questions are rephrased and asked again within the questionnaire in random order. For the answers, a 7-point Likert scale is used. The questions are asked in the following categories and the average of the subjects' responses to the questions in each category is used for evaluation (see Appendix C.2 for more information on the subjective scale):

- *Performance:* 3 questions are asked to the subjects to assess their self-performance.
- *Collaboration:* 2 questions investigate whether the subjects had a sense of collaborating with the robot or not.

- *Role exchange frequency:* A single question is asked to evaluate how frequently the subjects performed role exchanges.

- *Degree of control:* 2 questions ask the subjects about their perceived degree of control on the ball.

- *Interaction:* 5 questions explore the level of interaction the subjects experienced during the task.

- *Comfort and pleasure:* 4 questions investigate how comfortable and pleasurable the task was.

- *Haptic cues:* 1 question investigates whether haptic cues increased the subjects' awareness of their control level on the ball.

- *Visual cues:* 1 question investigates whether visual cues increased the subjects' awareness of their control level on the ball.

- *Trust:* 2 questions investigate if the subjects trusted their robotic partner on controlling the ball.

- *Ease of use:* 2 questions explore if the interface of the system was easy for the subjects to use.

- *Role exchange visibility:* A single question explores whether or not the subjects could observe the role exchanges during the task.

- *Humanlikeness:* 2 questions ask the subjects whether the forces felt through the device resembled that of a human.

3.4.6 Results

We present the results of the experiments in terms of the quantitative and subjective measures defined in Section 3.4.5. We also present the role exchange patterns observed under RE and VHC during the experiment.

Quantitative Analysis

During the experiments, we noticed that some of the subjects failed to perform the task as instructed. For instance, in some trials, the subjects worked against the robot and tried to hit the cylinders in the wrong order, causing an increase in energy consumption; in others, we observed a high number of faults, which causes the game to restart frequently and eventually results in significantly long completion times. Hence, we concluded that the data contains some outliers which should be addressed. Hence, prior to analysis, we detected the outliers in the data for each of the 7 independent quantitative measurements: completion time, number of faults, energy consumed by the human and the robot, the work done on the ball by the human, the robot, and the dyad. The detection of outliers in data is done by examining the boxplots generated by SPSS. In our outlier elimination procedure, we considered the samples as outliers if they were more than 3 interquartile ranges (IQR) away from the lower or upper quartiles. As a result, 1.6% of the data are identified as outliers and replaced with the grand mean values.

One-way repeated measures ANOVA is used to discover statistically significant effects of the guidance conditions. Mauchly's test was conducted to check if the assumption of sphericity was violated. If so, the degrees of freedom were corrected using Huynh-Feldt estimates of sphericity. Finally, post-hoc t-tests with Bonferroni correction were used for the multiple comparisons between conditions to assess which condition pairs exhibit statistically significant differences between one another.

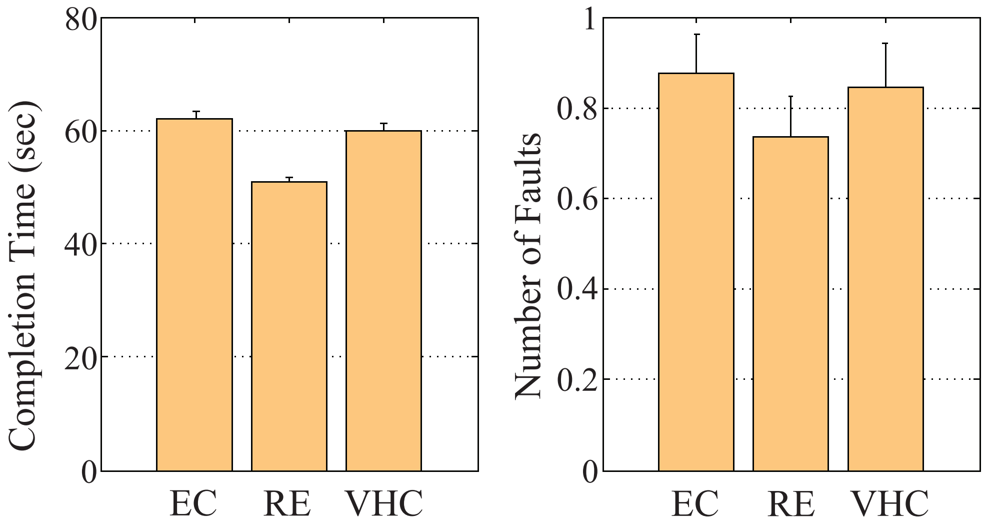


Figure 3.20: Average completion time and number of faults under each condition with SEM error bars (EC: Equal Control, RE: Role Exchange, VHC: RE with visual and haptic cues)

Task Performance

Figure 3.20 illustrates the mean completion times and the number of faults in each condition and the standard errors of the means (SEM). We observe that the completion time is the shortest under RE, followed by VHC and EC; and the number of faults is the least under RE, again followed by VHC and EC. We observe a significant effect of using the role exchange mechanism on completion time, however a similar effect is not observable on the number of faults done through the task (see Table 3.1). Although RE condition significantly improves the time performance, adding visual and vibrotactile cues on top of RE, as in VHC, deteriorates the performance significantly probably due to some extra cognitive effort (see Table 3.2).

Consumed Energy

Figure 3.21(a) shows the mean values of the energy consumed by the partners and the total energy consumed by the dyad under each condition. The error bars represent

Table 3.1: ANOVA results for completion time and number of faults

Source	df	F	p	$\eta^2_{partial}$
Time	1.685	24.617	.000	.142
Faults	2	.667	.514	.004

Table 3.2: The pairwise comparison of the guidance conditions for completion time and number of faults

	p-values		
	EC-RE	EC-VHC	RE-VHC
Time	.000(*)	.809	.000(*)
Faults	.759	1.000	1.000
* The mean difference is significant at p = .05 level.			

the standard error of the means.

We observe a significant effect of the guidance condition on the energy consumed by the human and the robot (see Table 3.3). We notice that the humans consume significantly more energy under RE and VHC than they do under EC (see Table 3.4). This indicates that the subjects consume some extra energy when they are presented with a role exchange scheme. Similarly, RE and VHC conditions exhibit similarities in the robot's energy consumption. Finally, we observe that the total energies consumed by the dyad under RE and VHC are significantly more than that of EC. This indicates that, the partners jointly spend more energy under a role exchange scheme.

Work Done on the Ball

In each trial, we computed the work done by the human and the robot on the ball. Figure 3.21(b) illustrates the means and the standard errors of the means for the work done on the ball under each condition. The guidance method has a significant effect on the work done by the human, the robot, and the dyad (see Table 3.5). We note

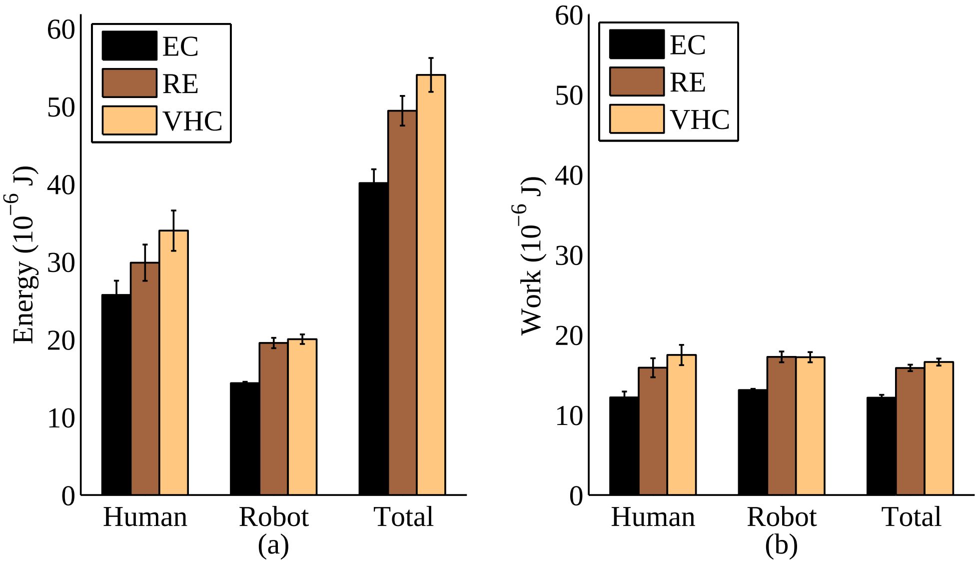


Figure 3.21: (a) average energy consumed and (b) the work done by the human, robot, and the dyad under each condition with SEM error bars (EC: Equal Control, RE: Role Exchange, VHC: RE with visual and haptic cues)

that the work done by the human under VHC and RE are significantly higher than that of EC. Similarly, the amounts of work done by the robot under RE and VHC are significantly higher than that of EC (see Table 3.6). This is another sign of the similarity in role exchange patterns in RE and VHC. The total work is significantly higher in VHC, followed by RE, and then EC; which means that beside spending more energy, the dyads also colectively do more work under RE and VHC.

In order to understand the role exchange patterns under RE and VHC, we examined the role exchange moments during the task under these two conditions.

Figure 3.22 illustrates the positions on the board that the users took control from the robot -Figures 3.22(a) and 3.22(c)- or handed over control to it - Figures 3.22(b) and 3.22(d) - during the experiment. These plots show the distribution of the role exchanges outside pit regions, as well as the distribution at the entrances and exits of the pits. It can be observed from the plots that the pits forced the users to exchange roles: In general, the users took control of the ball outside the pits to move faster. On

Table 3.3: ANOVA results for consumed energy (E_H: energy consumed by human, E_C: energy consumed by robot (i.e. the controller), E_{Total}: total energy)

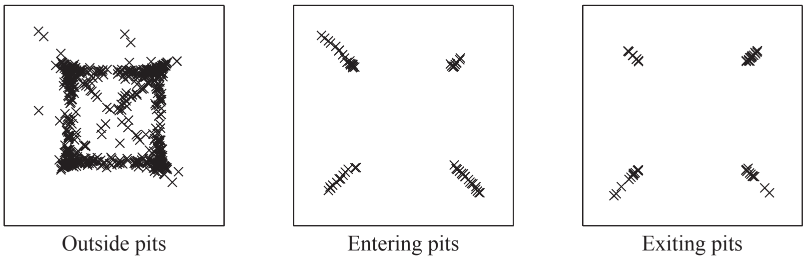
Source	df	F	p	$\eta^2_{partial}$
E_H	2	7.950	.000	.051
E_C	2	48.742	.000	.246
E_{Total}	1.945	27.094	.000	.154

Table 3.4: The pairwise comparison of the guidance conditions for consumed energy

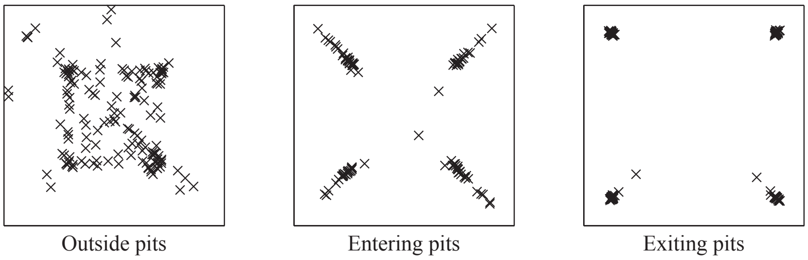
	p-values		
	EC-RE	EC-VHC	RE-VHC
E_H	.044(*)	.001(*)	.269
E_C	.000(*)	.000(*)	1.000
E_{Total}	.000(*)	.000(*)	.092
* The mean difference is significant at p = .05 level.			

Table 3.5: ANOVA results for work done on the ball (W_H: work done by the human, W_C: work done by the robot (i.e. the controller), W_{Total}: total work done by the dyad)

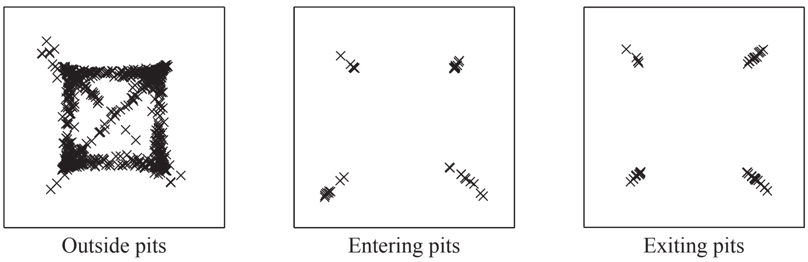
Source	df	F	p	$\eta^2_{partial}$
W_H	2	15.192	.000	.093
W_C	2	27.239	.000	.155
W_{Total}	2	84.953	.000	.363



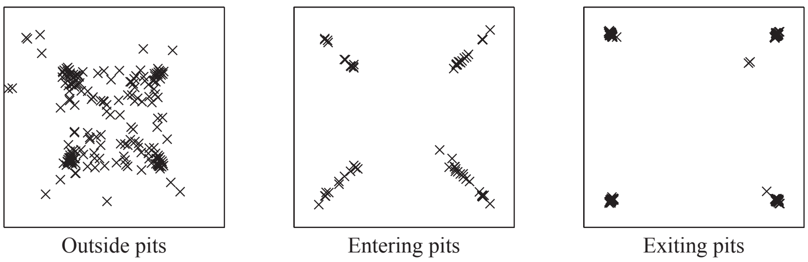
(a) user gets control (RE)



(b) robot gets control (RE)



(c) user gets control (VHC)



(d) robot gets control (VHC)

Figure 3.22: The positions on the board where role exchanges were initiated by the user during the game for guidance conditions RE and VHC. Note that the users tend to take control more often outside pit regions, whereas the robot takes control often when entering and exiting pits.

Table 3.6: The pairwise comparison of the guidance conditions for work done on the ball

	p-values		
	EC-RE	EC-VHC	RE-VHC
W_H	.042(*)	.000(*)	.318
W_C	.000(*)	.000(*)	1.000
W_{Total}	.000(*)	.000(*)	.048(*)
* The mean difference is significant at p = .05 level.			

the other hand, they frequently gave control to the robot when entering and exiting the pits to reduce the number of faults.

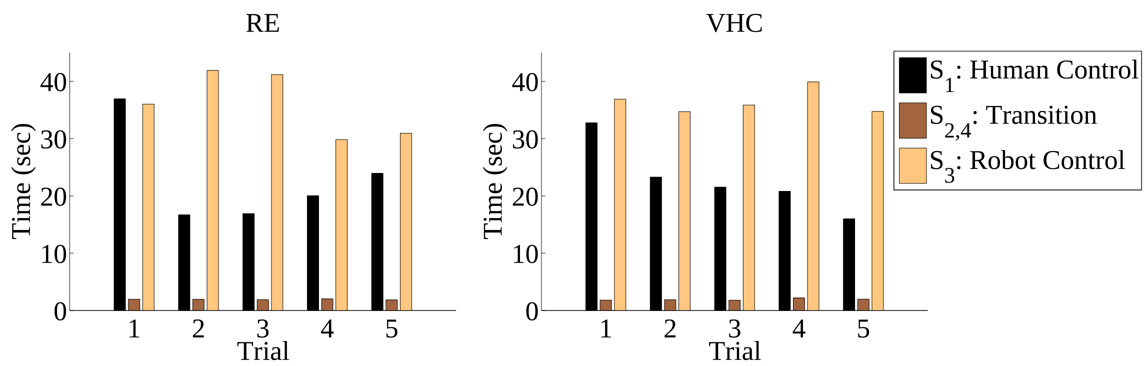


Figure 3.23: Average time spent in each state for 5 trials.

Also, we observed that the subjects typically decreased their contribution on the movement of the ball after the 1^{st} trial, taking advantage of robotic guidance until the end of the 5^{th} trial (see Figure 3.23). These observations indicate that the robot holds control for similar durations and at similar instants during the task in both RE and VHC.

Efficiency

Figure 3.24 displays the mean values of the efficiencies and the standard error of the means for each condition. The efficiency of the human under EC is significantly lower than that of both RE and VHC (see Table 3.8). On the other hand, we observe that the robot's efficiency is maximized under EC. This might suggest that as the subjects take less initiative in performing the task and mostly surrender to robotic guidance under EC, the energy consumed by the subjects and their work done is low. As a result of this, the human's efficiency decreases whereas that of the robot increases. However, the joint efficiency of the dyad under RE is significantly higher than that of EC. Even though the difference between the joint efficiencies under RE and VHC is not significant, the joint efficiency of the partners under VHC is slightly lower than it is under RE because of the extra energy consumed by the subjects under this condition.

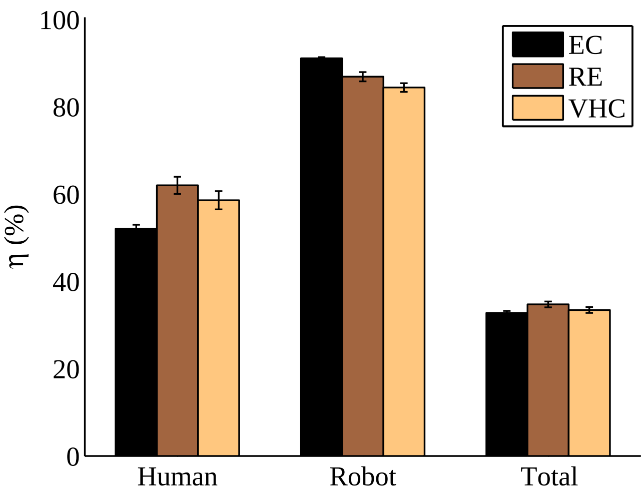


Figure 3.24: Average total efficiency and individual efficiencies of the human and the robot under each condition with SEM error bars

Table 3.7: ANOVA results for efficiency (η_H: efficiency of the human, η_C: efficiency of the robot (i.e. the controller), η_{Total}: joint efficiency of the dyad)

Source	df	F	p	$\eta^2_{partial}$
η_H	2	10.080	.000	.063
η_C	2	19.733	.000	.117
η_{Total}	2	3.094	.047	.020

Table 3.8: The pairwise comparison of the guidance conditions for efficiency

	p-values		
	EC-RE	EC-VHC	RE-VHC
η_H	.000(*)	.011(*)	.465
η_C	.001(*)	.000(*)	.085
η_{Total}	.027(*)	.866	.547
* The mean difference is significant at p = .05 level.			

Subjective Evaluation

Figure 3.25 plots the mean values of the subjects' responses to the questions in the questionnaire, as grouped in Section 3.4.5. Tables 3.9 and 3.10 present the ANOVA results and p-values for multiple comparisons.

The results can be summarized as follows:

- *Performance:* The users thought that they achieved the best performance under RE, followed by VHC and EC, however the differences between the conditions are not significant.

- *Collaboration:* The users reported that the sense of collaboration during the task was the most under VHC, followed by RE and EC, however the differences between the conditions are not significant.

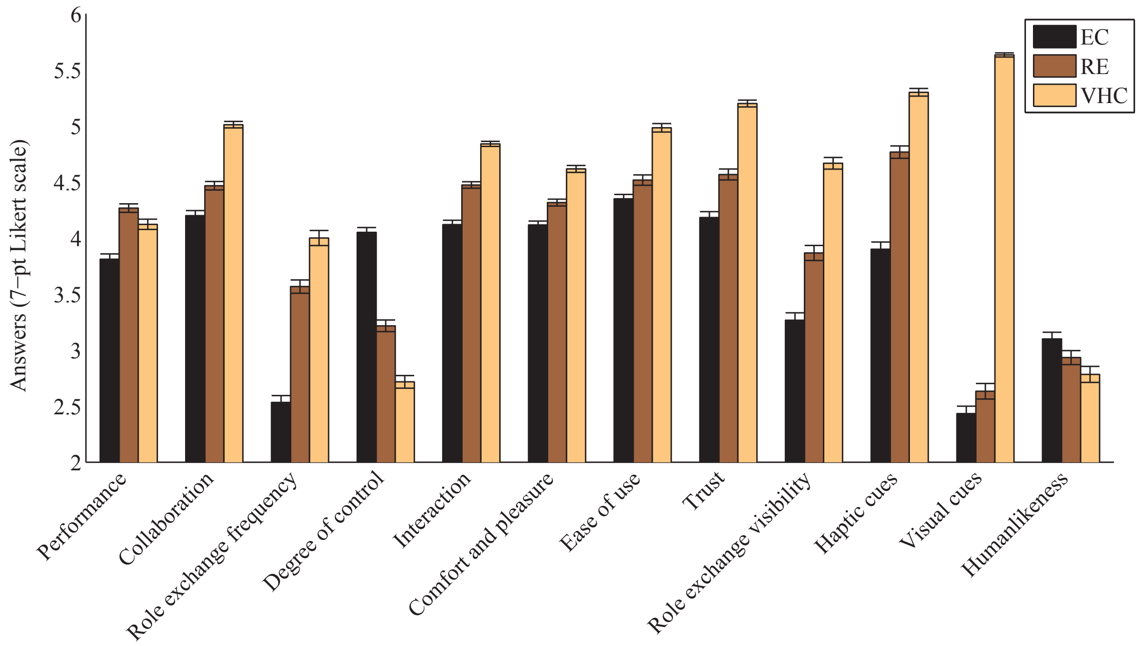


Figure 3.25: Means and standard errors of the subjective measures under each guidance condition.

- *Role exchange frequency:* The subjects believed that they effectively utilized the role exchange mechanism when applicable and they performed role exchanges equally frequently under RE and VHC. This indicates that the additional cues provided under VHC did not alter the strategies adopted by the subjects during the task.

- *Degree of control:* Under both RE and VHC, on the average, the subjects held control of the ball for about 37% of the total duration of the task. However, their perceived degree of control on the ball under EC was significantly higher than that of only VHC. This indicates that even though their control levels were similar under RE and VHC, the subjects could not clearly distinguish between different control levels when no informative cues were present. Hence, we conclude that the additional cues are successful in increasing the user's awareness.

- *Interaction:* The results suggest that the level of interaction during the task is

Table 3.9: ANOVA results for subjective measures

Source	df	F	p	$\eta^2_{partial}$
Performance	2	1.889	.160	.061
Collaboration	2	3.847	.027	.117
Role ex. frequency	1.747	8.671	.001	.230
Degree of control	2	7.992	.001	.216
Interaction	1.736	5.315	.011	.155
Comfort&pleasure	2	1.900	2.897	.063
Ease of use	2	3.959	.024	.120
Trust	2	4.306	.018	. 129
Role ex. visibility	2	6.324	.003	.179
Haptic cues	2	9.370	.000	.244
Visual cues	1.270	53.831	.000	.650
Humanlikeness	1.480	.470	.571	. 016

significantly higher when additional sensory cues are displayed to the users to signal the control state (VHC).

- *Ease of use:* The results suggest that the interface is significantly easier to use when additional cues are present (VHC).

- *Trust:* The RE mechanism let the users trust in their robotic partner during collaboration, such that they believe that the robot would move the ball correctly when needed. This sense of trust is significantly higher when additional sensory cues are present (VHC).

- *Role exchange visibility, the effect of additional sensory cues:* The subjects reported that when additional cues were present, the role exchange process was significantly more visible and they could understand the current state of the system better. They also reported that both visual and vibrotactile haptic cues

Table 3.10: The pairwise comparison of the guidance conditions for subjective measures

	p-values		
	EC-RE	EC-VHC	RE-VHC
Performance	.208	.796	1.000
Collaboration	1.000	.062	.094
Role ex. frequency	.031(*)	.005(*)	.374
Degree of control	.053	.005(*)	.265
Interaction	.499	.017(*)	.095
Comfort&pleasure	1.000	.091	.423
Ease of use	1.000	.032(*)	.232
Trust	.963	.033(*)	.109
Role ex. visibility	.312	.011(*)	.135
Haptic cues	.056	.001(*)	.242
Visual cues	.680	.000(*)	.000(*)
Humanlikeness	1.000	1.000	1.000
* The mean difference is significant at p = .05 level.			

were effective in enabling them to understand which party had control on the task. However, the visual cues are dominantly preferred by the subjects to determine the control state over the vibrotactile haptic cues.

- *Humanlikeness:* The users reported that none of the guidance conditions created a sense of interacting with a human partner. Interestingly, more than half of the subjects verbally stated that the control provided by the robot was too smooth to be human-like.

3.5 Discussion

This chapter summarizes the results of two experimental studies on the utility of a role exchange (RE) mechanism as a dynamic and personalized framework for human-robot collaboration. In this framework, a human dynamically interacts with a robotic partner by communicating through the haptic channel to trade control levels on the task.

We assume that robots are better than humans in terms of precision, hence it is reasonable to give control to the robot in case the user decreases the forces (s)he applies as an attempt to do fine-positioning. In order to take over the control, the users are required to generate only a sufficiently large displacement to exceed the force threshold. It is important to emphasize that once the user takes over the control, the spring constant between HIP and NIP is increased gradually, and the force applied to the user through the haptic device builds up smoothly and slowly. This causes the ball (virtually coupled to HIP, see Fig. Figure 3.1) to approach HIP, reducing the large displacement. Due to our blending approach and the simultaneous reduction in the distance between HIP and the ball, the increase in force magnitude can easily be handled by the users. During our experiments, the subjects did not report any instabilities or oscillations in the force response of the device.

Additionally, in Section 3.4, we propose the use of user-specific and dynamically adaptable force thresholds to initiate role exchanges. Since the adaptation process is transparent and the range of the force thresholds are narrow due to the limited output capacity of the haptic device, no user reported any inconsistency or difficulty in adapting to the newly calculated thresholds during the experiment.

The results summarized in Section 3.3 indicate that the role exchange mechanism presents the users with an option to choose and optimize between accuracy and energy when the users are not given any information on how to use the underlying mechanism (Oguz et al., 2010). However, we hypothesize that not knowing about the underlying mechanism makes it harder for the users to benefit from the RE mechanism. Hence, in Section 3.4 (also see (Kucukyilmaz et al., 2013)), we explain the role exchange mechanism to the users first and then evaluate their performance. Our results suggest that the proposed RE mechanism improves task performance when compared to the equal control guidance scheme (EC). Also, we observe that the efficiency of the users and the joint efficiency of the dyad are significantly higher under RE[6]. This implies that the users accomplish a higher amount of work with less effort when they are capable of exchanging roles with the robot. This indicates that the users can effectively benefit from a role exchange mechanism when they are explicitly instructed on the principles of interacting with the robot.

Additionally, in Section 3.4, we seek the benefits of supplementing the system with additional visual and vibrotactile cues to inform the users on the control state regarding the negotiation process. With the integration of these cues (VHC), we observe that task performance deteriorates, probably due to an extra cognitive load introduced by these cues. However, subjectively, the users report that these additional cues make the interface of the system easier to use, the task more interactive, and their robotic partner more trusted. Under both RE and VHC, we observe that the movement of the ball is predominantly controlled by the robot. Moreover, the role exchanges are performed at similar instants during the task and their numbers are

[6]Note that the collected data contains outliers, which are addressed before analyzing the data. The trends in our results remain intact regardless of whether we apply outlier elimination or not. In case no outliers are eliminated, we fail to observe any statistically significant differences between the performances achieved under different experimental conditions. On the other hand, the conclusions about the efficiency do not change.

close under both conditions. However, without the additional cues (under RE), we observe that the users may mistakenly think that they hold control of the ball more often then they do under VHC, whereas in reality the trends are similar under both conditions. This is a sign that additional cues are helpful in conveying the control state to the users.

Even though the studies presented in this chapter focuses only on human-robot cooperation in a virtual task, the proposed mechanism can also enhance the assistive capability of a robotic partner in physical cooperation with humans. In physical cooperation, two humans communicate dominantly through forces for negotiating action plans for accomplishing a task. Hence, communication through the haptic channel has promising implications in the context physical human-robot interaction. We suggest that as the robots are being more capable of performing a broader variety of tasks, more sophisticated robotic partners that can recognize and respond to the force signals acquired from the humans, will be built. In the next chapter, we will present our previous research on how a dynamic role exchange mechanism adds to the physical cooperation between a human and a robot.

Chapter 4

HUMAN-ROBOT COLLABORATION IN THE PHYSICAL WORLD

Despite the analogy between haptic shared control and physical human–robot interaction, defining roles and implementing the related role exchange mechanism is not straightforward when humans interact with a physical entity. In virtual shared control scenarios, approaches rely on adjusting either the coupling between the human operator and the virtual object or that between the human and the robotic assistant. On the other hand, physical interaction with robotic assistants procludes the possibility of controlling the human's coupling with the object and the coupling between partners. This section presents our efforts to enable haptic negotiation and exchange of roles during physical cooperation with a human-sized robotic assitant (Moertl et al., 2012).

4.1 Design Approach and Application

The scenario we presented in (Moertl et al., 2012) involves the collaboration of a human and an assistive robot. In coarse terms, we program a robot to jointly manipulate a rigid bulky object along with a human (see Figure 4.1).

During joint manipulation, cooperating agents typically communicate to share the physical effort required to finish the task. Such effort sharing indicate role allocation (RA) strategies between partners. In order to achieve efficient RA in man-machine systems, the physical coupling imposed by the task's geometrical and dynamical properties has to be addressed.

We confine the role allocation problem in physical HRI to the following conditions:

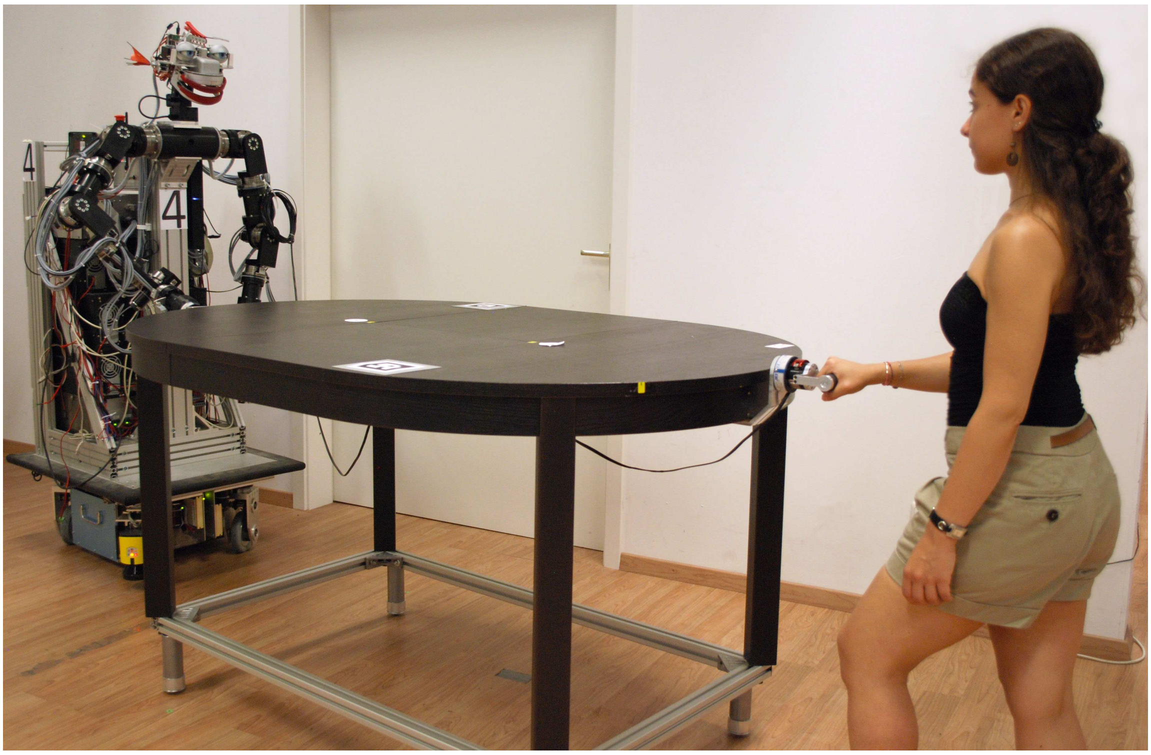


Figure 4.1: Cooperative manipulation scenario: A human carries a table cooperatively with a robot.

1. One human cooperates with one robot or system of robots with centralized communication towards achieving a common known goal (e.g. reaching certain target configuration(s) while jointly manipulating an object).

2. The task is achievable (e.g. a feasible path to the target exists at all times).

3. All agents *tightly grasp* a single *rigid* object with commonly known shape and dynamics.

4. Object dynamics are holonomic, i.e. the manipulated system does not have any velocity-dependent constraints.

5. The grasp points are such that the task is *controllable* and its control inputs are *redundant* (Lawitzky et al., 2010).

6. The partners interact with each other only through the haptic channel provided by the physical coupling.

4.1.1 System-theoretic modeling approach

We simplify our problem by assuming shared goals in terms of mutually known intermediate configurations for the dyad. Research on dyadic human cooperation suggests that partners can achieve better tracking performance in a cooperative task when they have common visual access to the central part of a manipulated object (Salleh et al., 2011). Thus, the desired motion of the manipulated object can be intuitively represented by an object-centered trajectory as a result of a priori negotiation between the agents. A trajectory for the cooperating dyad can be precomputed by the robot via planning as proposed by Kirsch et al. (2010) or from human demonstration (Medina et al., 2011). To ensure tracking of the desired object trajectory, we employ partners with an impedence control loop closed on motion feedback. Furthermore, we assume that the object model is known to all agents.

In order to obtain the required individual control inputs for motion tracking, each agent uses the inverse dynamics model of the object. While the human motor control system is known to accomplish haptic tasks by a combination of impedance control and inverse dynamics model of the task (see e.g. Franklin et al., 2003), automatic parameter acquisition for rigid body loads is a difficult problem, which has been frequently discussed in the literature since Atkeson et al. (1986). Also state-of-the-art methods require structural knowledge of friction. Therefore, we adopt a dynamic modeling approach to define the physical and geometrical properties of the manipulation task under environmental constraints. We model the dynamics of the manipulated object using the agents' grasp points, where each agent's contributions to the task can be defined by individual wrenches (i.e.forces) they apply on the object.

This is where the demand for a role allocation strategy comes into play. Role allocation describes the distribution of voluntary force inputs among agents. Each agent can be assigned a certain input behavior in terms of an effort sharing policy.

The behavioral patterns of the agents due to a certain effort sharing policy can be referred to as *roles* that the agents take on in the redundant task space. Redundancies of the control inputs, which are usually present when two or more agents manipulate a single object (Lawitzky et al., 2010), span a subspace of the control inputs which can be deliberately distributed between the agents without affecting the motion.

An investigation of human cooperative behavior in a dyadic tracking tasks provides evidence for the existence of role distributions, which are partly person-specific and partly interaction-dependent (Groten et al., 2009). The effort-role behavior we synthesized in (Moertl et al., 2012) is embedded in the interaction control loop and mediates the robot's control inputs to the task. If we assume persistent validity of the agents' shared plan within a static environment, the input applied by a *single human* can be estimated based on the object dynamics, and can be fed back to update the role allocation strategy adopted by the agents. Figure 4.2 illustrates our approach.

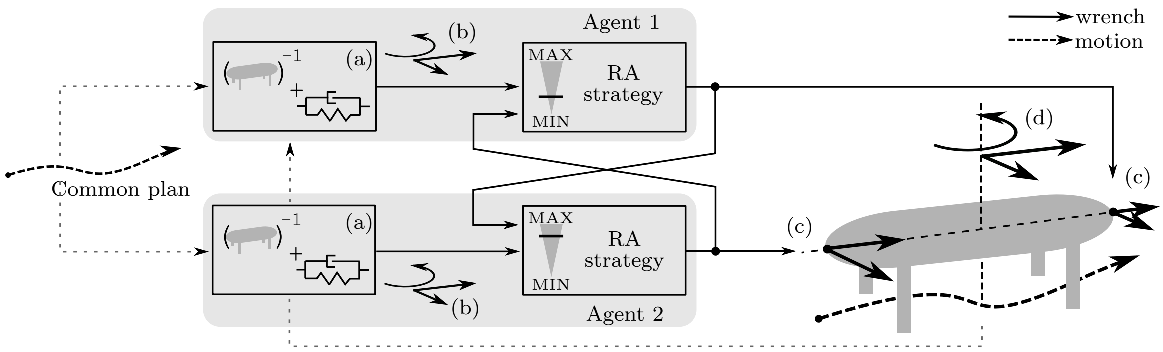


Figure 4.2: Overview of the modeling approach: Agent 1 and Agent 2 cooperatively manipulate an object according to a shared plan. Both agents use an inverse object model and an impedance control loop (a) to generate desired object-centered wrenches (b). Agents' role allocation (RA) strategies affect the control inputs (i.e. wrenches) they apply at the grasp points (c), which form the object-centered wrench (d) required for motion tracking. During interaction, RA strategies are updated continuously due to mutual feedback of the control inputs.

4.2 Synthesis of Role Behavior

This section presents the object model and the parametrization of the effort-sharing policies. Role definitions and details of the policies that are used in the experiments are explained. Our method of parametrization the effort-sharing policies generalizes to multiple cooperating partners. Therefore, in the first part of the derivations, we will keep the method as general as possible and later specialize to the dyadic case.

4.2.1 Notation

In the rest of this chapter, we use the wrench representation[1]. Bold characters are used for denoting vectors and matrices. $\mathrm{Ker}(\boldsymbol{A})$ denotes the nullspace (kernel) of matrix $\boldsymbol{A}$. $\mathrm{Ker}_j(\boldsymbol{A})$ denotes the j^{th} vector spanning $\boldsymbol{A}$'s nullspace. *Nullity* is the dimension of a matrix' nullspace. Superscripts are used to denote the reference frame of the respective matrix and vector quantities, whereas quantities referring to the inertial (world) frame are written without superscripts.

4.2.2 Object model

The problem of joint object transfer in its general form involves the contribution of N agents that tightly grasp a rigid object of arbitrary shape as shown in Figure 4.3. In the figure, a body frame C is attached to the object and the inertial frame is denoted by I.

In the rest of this section, we present a system-theoretic analysis of the task regarding the dynamical and geometrical model of the manipulated object, i.e. the coupling between the agents.

The rigid-body dynamics of the object can be described by

$$\boldsymbol{M}_c\ddot{\boldsymbol{x}}_c + \boldsymbol{f}_c(\boldsymbol{x}_c, \dot{\boldsymbol{x}}_c) = \boldsymbol{u}_c, \tag{4.1}$$

[1] According to Poinsot's theorem, a wrench is equivalent to a single force applied along a line, combined with a torque about that same line.

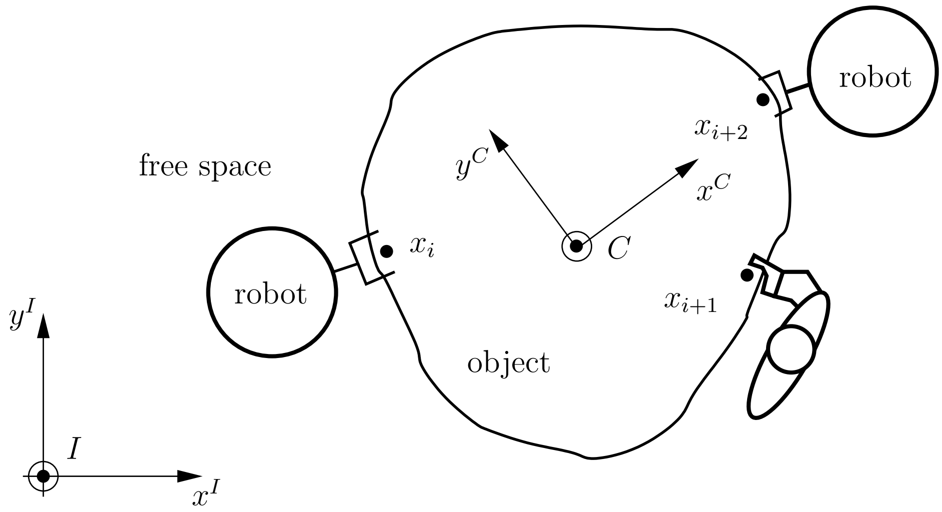


Figure 4.3: Haptic human-robot joint action task: Cooperative manipulation of a rigid object by multiple agents acting at different grasp points.

where $\boldsymbol{x}_c$ is the configuration of the object with inertia $\boldsymbol{M}_c$, $\boldsymbol{f}_c$ is the sum of environmental forces such as friction and gravitation, and $\boldsymbol{u}_c$ denotes the *external wrench* applied by the agents to the object.

Agent i ($i = 1, ..., N$) contributes to the manipulation task via input wrench $\boldsymbol{u}_i$ applied at the grasp point $\boldsymbol{x}_i$ on the object. In order to formally represent the grasp and to consider only the efficient input wrench components applied by the agents, we define *applied wrench* $\tilde{\boldsymbol{u}}_i$ as

$$\tilde{\boldsymbol{u}}_i = \boldsymbol{R}\boldsymbol{B}_i\boldsymbol{R}^T\boldsymbol{u}_i, \tag{4.2}$$

where $\boldsymbol{R}$ denotes the rotation of frame C w.r.t. I and $\boldsymbol{B}_i$ is a selection matrix referred to the body frame C with elements $b_{k,l} \in \{0, 1\}$ that determine which independent torque and force components an agent can effectively apply at the grasp point. Note that $\boldsymbol{B}_i$ is also known as wrench basis in grasp analysis (Murray et al., 1994). Thus, the external wrench on the object is composed by

$$\boldsymbol{u}_c = \sum_{i=1}^{N} \boldsymbol{G}_i\tilde{\boldsymbol{u}}_i, \tag{4.3}$$

where $\boldsymbol{G}_i$ is a matrix of size $\dim(\tilde{\boldsymbol{u}}_i)\times\dim(\boldsymbol{u}_c)$, and denotes the partial grasp matrix given by the Jacobian of the kinematic constraints $\boldsymbol{\phi}_i(\boldsymbol{x}_c)$ (Prattichizzo and Trinkle, 2008). $\boldsymbol{\phi}_i(\boldsymbol{x}_c)$ describes the position of the rigid grasp point with respect to the object frame. The kinematics comprising position $\boldsymbol{x}_i$ and velocity $\dot{\boldsymbol{x}}_i$ of the grasp point of agent i are

$$\boldsymbol{x}_i = \boldsymbol{\phi}_i(\boldsymbol{x}_c) \tag{4.4}$$

$$\dot{\boldsymbol{x}}_i = \boldsymbol{G}_i^T \dot{\boldsymbol{x}}_c. \tag{4.5}$$

4.2.3 Effort sharing by input decomposition

In this section, we develop an effort sharing strategy which utilizes *redundant* degrees of freedom that naturally arise from actuation redundancy. According to the system-theoretic approach outlined in Section 4.1.1, a desired external wrench $\hat{\boldsymbol{u}}_c$ can be calculated using the inverse dynamical system model (Equation (4.1)). $\hat{\boldsymbol{u}}_c$ is the desired wrench to be imposed on the object to track a shared plan given by a desired object trajectory $\boldsymbol{x}_{c,d}$. Note that in general, only parts of the applied wrenches cause object motion and hence constitute the external wrench. The remaining component of the applied wrench is called *internal wrench* and causes squeeze forces on the object. In the next step, we aim for solutions of each agent's applied wrench $\tilde{\boldsymbol{u}}_i$, in order to compose a desired $\hat{\boldsymbol{u}}_c$.

By substituting Equation (4.3) into Equation (4.1), we obtain the object model

$$\boldsymbol{M}_c\ddot{\boldsymbol{x}}_c + \boldsymbol{f}_c(\boldsymbol{x}_c, \dot{\boldsymbol{x}}_c) = \boldsymbol{G}\tilde{\boldsymbol{u}}, \tag{4.6}$$

where the complete grasp matrix $\boldsymbol{G}$ is composed by the block diagonal matrix

$$\boldsymbol{G} = \operatorname{diag}\left\{ \begin{array}{ccc} \boldsymbol{G}_1, & \dots, & \boldsymbol{G}_N \end{array} \right\},$$

and $\tilde{\boldsymbol{u}}$ represents the stacked applied wrench

$$\tilde{\boldsymbol{u}} = \left[\begin{array}{ccc} \tilde{\boldsymbol{u}}_1 & \dots & \tilde{\boldsymbol{u}}_N \end{array} \right]^T.$$

Let us introduce

$$\tilde{\boldsymbol{u}} = \boldsymbol{A}\hat{\boldsymbol{u}}_c, \tag{4.7}$$

where $\boldsymbol{A}$ denotes the decomposition matrix that transforms desired external wrenches to applied wrenches.

Using Equations (4.6) and (4.7), the dynamical object model depending on the desired external wrench yields

$$\boldsymbol{M}_c\ddot{\boldsymbol{x}}_c + \boldsymbol{f}_c(\dot{\boldsymbol{x}}_c) = \boldsymbol{G}\boldsymbol{A}\hat{\boldsymbol{u}}_c.$$

In order to achieve tracking of the desired trajectory through feed-forward control of the inverse dynamics, matrix $\boldsymbol{A}$ has to be chosen to sustain $\boldsymbol{u}_c = \hat{\boldsymbol{u}}_c$, i.e. $\boldsymbol{A}$ has to be an inverse of $\boldsymbol{G}$, fulfilling

$$\boldsymbol{G}\boldsymbol{A} = \boldsymbol{I}. \tag{4.8}$$

Note that $\dim(\boldsymbol{u_c})$ is equal to the dimension of the object's configuration space, $\dim(\boldsymbol{x}_c)$, since the task is required to be controllable and holonomic. In our setting, we further assume that the number of actual inputs is larger than the required number of inputs for task completion:

$$\dim(\tilde{\boldsymbol{u}}) > \dim(\boldsymbol{u}_c).$$

A minimal example of such actuation redundancy is the movement of an object in one-dimensional space by two agents, each applying an input wrench. The task is redundant as one agent's input would be sufficient for controlling the object and arbitrary compositions of the agent's input forces are possible, see Figure 4.4. Therefore, the choice of $\boldsymbol{A}$ in Equation (4.8) is not unique.

We can show that a particularly interesting solution for the effort-sharing matrix $\boldsymbol{A}$ is the generalized *Moore-Penrose* pseudoinverse $\boldsymbol{G}^+$ of the complete grasp matrix $\boldsymbol{G}$, which yields the minimum-norm solution for $\|\tilde{\boldsymbol{u}}\|$ (Doty et al., 1993). Since we are solving for wrenches, there is particular physical meaning of the minimum-norm solution:

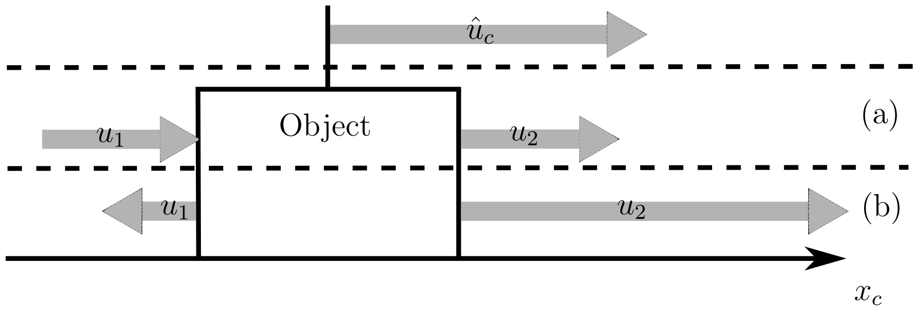


Figure 4.4: Illustrative example of input decomposition in a one-dimensional redundant task. (a) minimum-norm solution. (b) possible, but inefficient solution.

The applied wrench obtained with $\boldsymbol{G}^+$ represents an *efficient* decomposition as the external wrench is composed by a minimum magnitude of the individual applied wrench components (see Figure 4.4 (a)). Hence, the applied wrench has no components which could cause ineffective internal wrenches.

Replacing $\boldsymbol{A}$ with $\boldsymbol{G}^+$ in Equation (4.7), the family of all solutions for $\tilde{\boldsymbol{u}}$ is given by

$$\tilde{\boldsymbol{u}} = \boldsymbol{G}^+\hat{\boldsymbol{u}}_{\boldsymbol{c}} + \sum_{j=1}^{\text{nullity}(\boldsymbol{G})} \lambda_j \text{Ker}_j(\boldsymbol{G}), \tag{4.9}$$

where $\lambda_j \in \mathbb{R}$ and $\text{Ker}_j(\boldsymbol{G})$ denotes the j^{th} vector spanning $\boldsymbol{G}$'s nullspace. The nullspace of $\boldsymbol{G}$ provides a solution space for $\tilde{\boldsymbol{u}}$:

$$\text{Ker}(\boldsymbol{G}) = \{\tilde{\boldsymbol{u}} | \boldsymbol{G}\tilde{\boldsymbol{u}} = \boldsymbol{0}\}$$

Note that in terms of physical meaning, the null-space component does not affect the motion of the object, as it does not change the external wrench on the object.

Depending on the choice of λ_j, $\tilde{\boldsymbol{u}}$ potentially produces internal wrenches, as depicted in Figure 4.4 (b). In fact, Equation (4.9) provides an effort sharing strategy by input decomposition: (1) In *redundant* degrees of freedom where effort sharing between the agents is determined by λ_j, and (2)in *non-redundant* degrees of freedom, where each agent's input is uniquely defined by a necessary contribution.

In the following section, we show how λ_j can be used to parameterize the effort sharing strategy between the agents in a 2-dimensional task with a single redundant direction.

4.2.4 Policies for effort sharing

In this section, we show how the agents can be assigned meaningful policies regarding their effort behavior in a single redundant degree of freedom. With reference to the experiment conducted in our study and for intuitiveness of analysis, we consider from this section on a planar cooperative manipulation task involving two agents for the design of effort sharing policies without loss of generality. The presented strategy may be conducted in multiple redundant degrees of freedom.

Analysis of a planar dyadic task

An example planar dyadic task is shown in Figure 4.5, which satisfies the requirements from Section 4.1. Such a task can be exemplified as the joint transportation of a large table on ball casters, or the joint manipulation of any other heavy object which is slided on a surface.

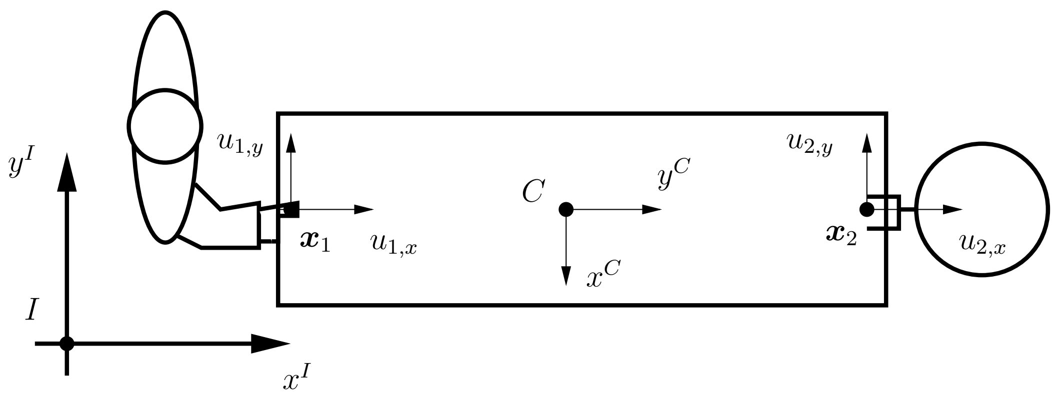


Figure 4.5: A planar cooperative manipulation scenario: one human (left) and one robot (right) jointly move a bulky object in the x-y-plane.

During the task, the human (i=1) and the robotic agent (i=2) provide input wrenches $\boldsymbol{u}_i$ of dimension $\dim(\boldsymbol{x}_c)$, where

$$\boldsymbol{x}_c = \begin{bmatrix} x_{c,\phi} & x_{c,x} & x_{c,y} \end{bmatrix}^T.$$

These input wrenches generally include torques. However, a common property of bulky objects regarding their handling is the lack of sensitivity of object dynamics to certain torque components. This indicates that these torques cannot be applied effectively at the grasp points (See also Wojtara et al., 2009). This can be explained within our illustrative scenario: Assume a beam-like bulky object with a long geometrical axis, which is manipulated by two partners using a single-handed grasp on the each end of the object, see Figure 4.5. Practically, it is rather cumbersome to apply the torque required to induce a desired rotational motion around the z^C-axis through the wrist. On the other hand, it is much easier to apply an appropriate force through the whole arm, which induces turning by translational motion of the grasp point.

Since our analysis focuses on the primary effects of the system's redundant degrees of freedom for effort sharing, the wrench basis

$$\boldsymbol{B}_{1,2} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

is chosen in our illustrative scenario. Putting it into Equation (4.2) reduces the input wrench to the effectively applied wrench

$$\tilde{\boldsymbol{u}} = \begin{bmatrix} u_{1,x} & u_{1,y} & u_{2,x} & u_{2,y} \end{bmatrix}^T. \tag{4.10}$$

The kinematic constraints of the system defined by Equation (4.4) can be written as

$$\boldsymbol{x}_i = \begin{bmatrix} x_{c,x} & x_{c,y} \end{bmatrix}^T - \boldsymbol{R}\boldsymbol{r}_{ic}^C,$$

with

$$\boldsymbol{R} = \begin{bmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{bmatrix},$$

denoting the rotation of object frame C w.r.t. inertial frame I by angle ϕ, and the vectors from the grasp point of agent i to the origin of C:

$$\boldsymbol{r}_{ic}^{C} = \begin{bmatrix} r_{ic,x} & r_{ic,y} \end{bmatrix}^T$$

According to Equation (4.5), the 4×3 transpose of the grasp matrix can be derived as:

$$\boldsymbol{G}^T = \begin{bmatrix} \sin\phi\, r_{1c,x} + \cos\phi\, r_{1c,y} & 1 & 0 \\ -\cos\phi\, r_{1c,x} + \sin\phi\, r_{1c,y} & 0 & 1 \\ \sin\phi\, r_{2c,x} + \cos\phi\, r_{2c,y} & 1 & 0 \\ -\cos\phi\, r_{2c,x} + \sin\phi\, r_{2c,y} & 0 & 1 \end{bmatrix}. \tag{4.11}$$

Our planar system is redundant regarding the applied wrench, defined by Equation (4.10) since $\dim(\boldsymbol{x}_c) = \mathrm{rank}(\boldsymbol{G}) = 3$ for different grasp constraints $\boldsymbol{r}_{1,c} \neq \boldsymbol{r}_{2,c} \neq \boldsymbol{0}$, and $\dim(\tilde{\boldsymbol{u}}) = 4$. Thus, parts of the task effort in terms of applied wrenches can be shared arbitrarily among the contributing agents within the redundant degree of freedom without influence on the external wrench of the object.

Identification of meaningful policies

In this section, we introduce *effort sharing policies* which are described by a certain choice of the parameter λ in Equation (4.9) in order to characterize meaningful shares. Firstly, we investigate static sharing policies yielding constant role behaviors, while in Section 4.2.5 we extend our notion of roles to encompass a dynamic allocation within dyads.

In the given planar example, the only redundant degree of freedom is intuitively represented by the y^C-axis of the object frame C (c.f. Figure 4.5), hence components of the external input wrench along this axis can be arbitrarily shared among the two agents. Let us recall the decomposition in Equation (4.9), which define the agents' applied wrenches $\tilde{\boldsymbol{u}}$. The nullspace $\mathrm{Ker}(\boldsymbol{G})$ is spanned by the family

$$\mathrm{Ker}(\boldsymbol{G}) = \mathrm{diag}\left(\boldsymbol{R}, \boldsymbol{R}\right)\, \mathrm{Ker}(\boldsymbol{G})^C, \tag{4.12}$$

with

$$\mathrm{Ker}(\boldsymbol{G})^C = \begin{bmatrix} 0 & 1 & 0 & -1 \end{bmatrix}^T, \tag{4.13}$$

allowing one degree of freedom for the design of different effort sharing policies through the choice of the scalar parameter λ in Equation (4.9)[2]. Three extreme policies of particular physical meaning are discussed below:

- *Balanced-effort policy:* By choosing the policy

  $$\pi_{bal} : \lambda = 0, \tag{4.14}$$

  we obtain the min-norm solution for $\tilde{\boldsymbol{u}}$. The effort in terms of magnitude of the applied wrench is to be equally shared among the agents, see Figure 4.6(a).

- *Maximum-robot-effort policy:* In order for the robot to take over all of the sharable effort, the applied human force in the y^C-direction is assumed to be zero, i.e. $\tilde{u}^C_{1,y} = 0$. Hence, λ is chosen in a way that the human does not contribute any *voluntary* effort to the task and all voluntary effort is undertaken by the robot, which yields the policy

  $$\pi_{max} : \lambda = -\begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} \tilde{\boldsymbol{u}}^C_{bal}, \tag{4.15}$$

  with the min-norm applied wrench

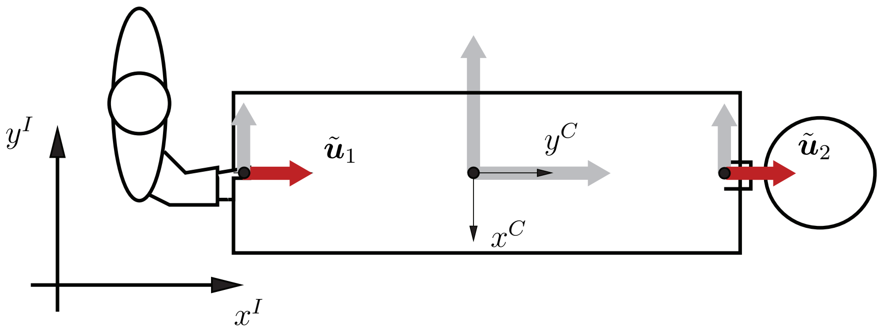
  $$\tilde{\boldsymbol{u}}^C_{bal} = \mathrm{diag}\left(\boldsymbol{R}, \boldsymbol{R}\right)^T \boldsymbol{G}^+ \hat{\boldsymbol{u}}_{\boldsymbol{c}}. \tag{4.16}$$

  This policy minimizes the magnitude of the required human effort in terms of the Euclidean norm

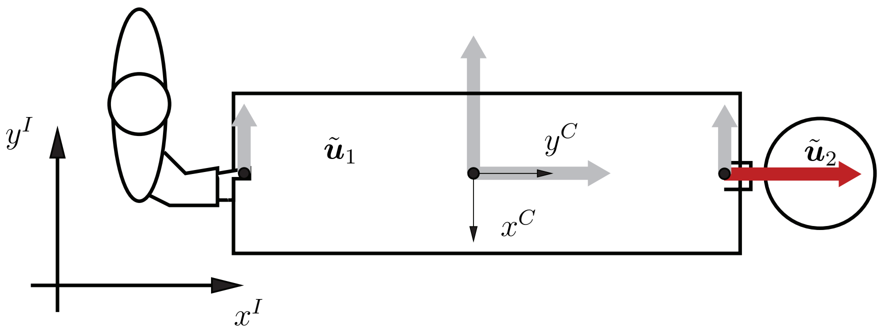
  $$\|\tilde{\boldsymbol{u}}^C_1\| = \sqrt{(\tilde{u}^C_{1,x})^2 + (\tilde{u}^C_{1,y})^2},$$

  where $\tilde{u}^C_{1,x}$ and $\tilde{u}^C_{1,y}$ refer respectively to the necessary and voluntary input contributions (see Figure 4.6(b)). Intuitively spoken, the human has to apply wrenches only in those degrees of freedom, in which the task simply *can not* be accomplished by the robot alone, i.e. rotation, and motion in x^C-direction.

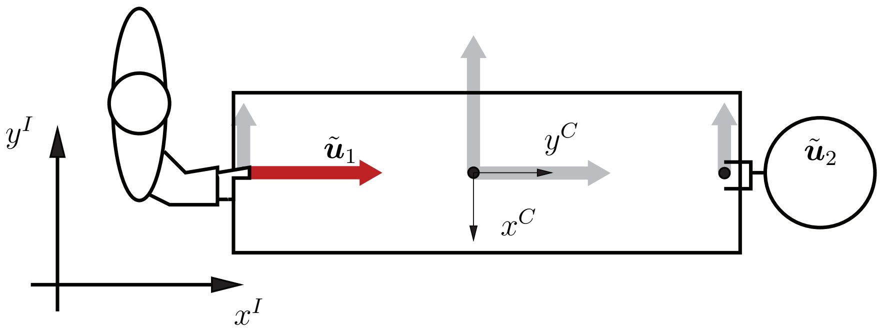
[2]The roles and the allocation strategy refer to a task's redundant degree of freedom. With multiple redundant degrees of freedom, role allocations between the partners may differ.



(a) Equal share of the voluntary effort.



(b) Robot takes all of the voluntary effort.



(c) Human takes all of the voluntary effort.

Figure 4.6: Given exemplary external wrench realized by three different effort policies.

- *Minimum-robot-effort policy:* Dual to policy π_{max}, with this policy, we assume that the human has to take over all of the sharable effort by satisfying $\tilde{u}^C_{2,y} = 0$:

$$\pi_{min} : \lambda = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} \tilde{\boldsymbol{u}}^C_{bal}, \tag{4.17}$$

where $\tilde{\boldsymbol{u}}^C$ is given by Equation (4.16). Using this policy results in a minimum-effort robot assistance, i.e. in both degrees of freedom, the human has to apply the wrench components necessary to accomplish the task (see Figure 4.6(c)).

We generalize the family of effort sharing policies with the use of a single *policy parameter* $\alpha \in \mathbb{R}$

$$\pi : \lambda = -\alpha \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} \tilde{\boldsymbol{u}}_{bal}^{C}, \tag{4.18}$$

Obviously, the policies π_{bal}, π_{max} and π_{min} are parameterized by setting $\alpha = 0$, $\alpha = 1$ and $\alpha = -1$ respectively.

Note: Policies defined by Equation (4.18) with $\alpha \in [-1; 1]$ and the kernel family parameterized by Equation (4.13) are efficient, since no counter-acting internal wrench on the object is generated. Figures 4.6(b) and 4.6(c) depict the extreme, yet still efficient cases for $|\alpha| = 1$, which are obtained intuitively from Figure 4.6(a) by shifting the voluntary effort. Setting $|\alpha| > 1$ generates counter-acting wrenches, c.f.Figure 4.4 (b).

4.2.5 Dynamicallocation of roles

The effort sharing policies Equation (4.18) with constant policy parameter α imply a *static role* in terms of the effort sharing between the dyad in the redundant direction, which results from a feedforward calculation of the agents' applied wrenches. In contrast, a *dynamic role allocation* strategy as investigated here varies the policy parameter α over time depending on the measured *wrench of the partner*. In the dyadic case, the robotic agent may estimate its partner's applied wrench if the object's dynamics (Equation (4.1)) and kinematics (Equations (4.4) and (4.5)) are known to the robot. In Section 4.3.1 we provide details on such an estimation strategy.

The resulting robot behavior in terms of its urge to complete the task is influenced by the velocity profile of the configuration trajectories planned by the robot. Velocity profiles can be taken from observations in human-human experiments, can describe the technical limitations of the robotic system in its environment, or can be a mixture of both. Kinodynamic motion planning techniques can alternatively be used to produce trajectories with bounds on velocities and accelerations (Donald et al., 1993) in order to generalize the approach to arbitrary feasible transport tasks.

Constant role allocation (CRA)

As a baseline strategy, we propose constant allocation of roles during the task. Any arbitrary choice of a constant α parameter directly affects the robot's urge to accomplish the task. In particular, $\alpha = 0$ results in an equal, feedforward composition of the external wrench in the redundant degree of freedom. This scenario presents a symmetric case: A human partner applying the same wrench as the robot in the redundant degree of freedom moves the object according to the robot's velocity profile. In contrast, a human partner who applies the same wrench in the opposite direction cancels the robot's applied wrench.

Weighted proactive role allocation (WPRA)

For the realization of the weighted role allocation strategy developed in this work, we propose a continuous, first order dynamical system with the policy parameter bounded within the interval $[-1, 1]$ by an anti-windup saturation to obtain only the efficient policies:

$$\alpha = \alpha_0 + \int_{t_0}^{t} \dot{\alpha} dt, \tag{4.19}$$

The derivative $\dot{\alpha}$ is set regarding the value of the agreement indicator

$$\xi = \begin{cases} 0, & \text{if } \operatorname{sgn}(\tilde{u}^C_{1,y}) \neq \operatorname{sgn}(\tilde{u}^C_{1,y,est}) \neq 0 \\ 1, & \text{otherwise} \end{cases} \tag{4.20}$$

and is weighed by the feedback of the human wrench component $\tilde{u}^C_{1,y,est}$ in the redundant direction, which yields a role allocation with a progressively changing policy depending on the magnitude of the partner's contribution.

$$\dot{\alpha} = \begin{cases} \tau_{-,w} \left|\tilde{u}^C_{1,y,est}\right|, & \text{if } \xi = 0 \\ \tau_{+,w}\, \tilde{u}^C_{y,thr}, & \text{if } \xi = 1 \wedge \left|\tilde{u}^C_{1,y,est}\right| < \tilde{u}^C_{y,thr} \\ \tau_{+,w} \left|\tilde{u}^C_{1,y,est}\right| & \text{otherwise} \end{cases}.$$

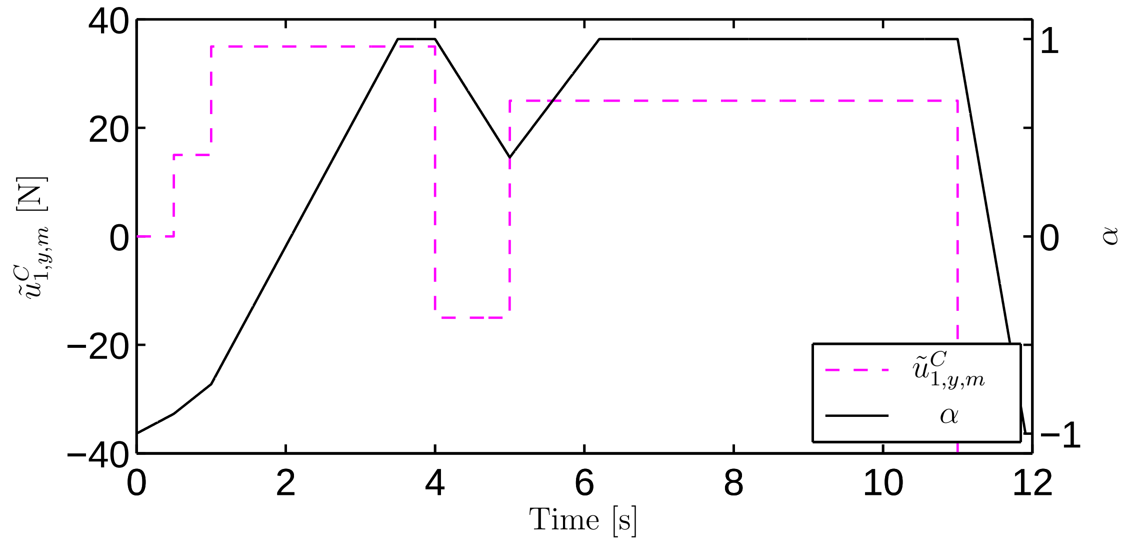
Note that the initial value $\alpha_0 = -1$ produces a minimum-robot-effort behavior. The agreement value of $\xi = 1$ is produced either by a wrench input $\tilde{u}^C_{1,y,est}$ in the expected direction $\mathrm{sgn}(\tilde{u}^C_{1,y})$ or when the human is inactive. If $\xi = 1$, the policy parameter α is increased, which leads to emerging robot effort. A threshold $\tilde{u}^C_{y,thr}$ is used to define neutral human wrench input which is treated as silent agreement. The constants $\tau_{-,w}$ and $\tau_{+,w}$ weigh the human's agreement or disagreement force input. A faster reaction to disagreement signals (i.e. $-\tau_{-,w} > \tau_{+,w} > 0$) is considered to be a reasonable option. This choice lets the robot rapidly fall back to minimum effort if the human signals discomfort by applying a counteracting force. The dynamical behavior of the weighted role allocation scheme is illustrated by a simulation example in Figure 4.7(a).

Discrete role allocation

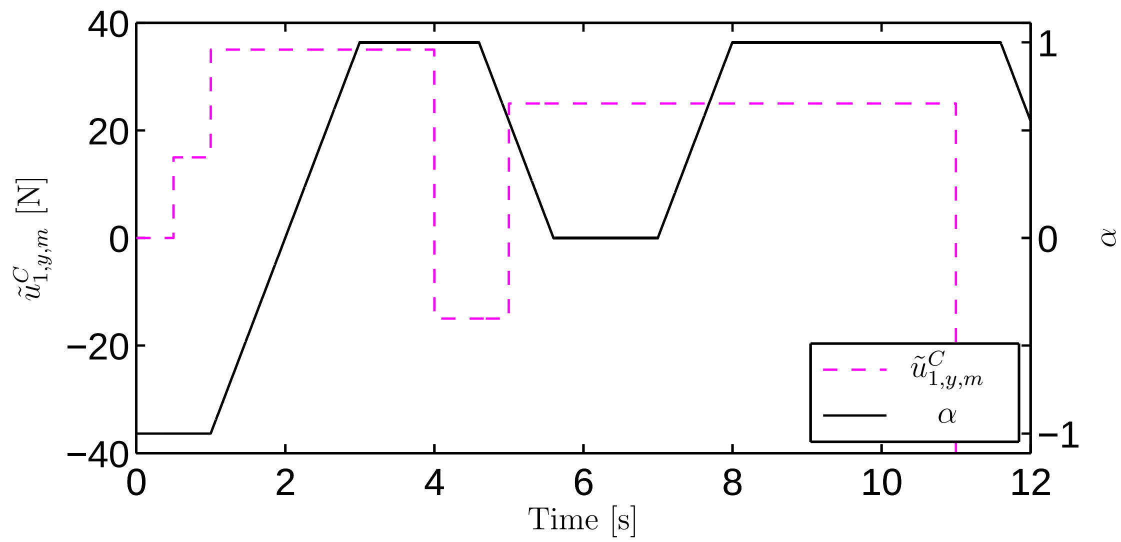
In order to investigate whether role allocation with a small number of distinct meaningful steps is more understandable for the human partner and hence beneficial for cooperation, a discrete version of the continuous role allocation mechanism is developed. A chattering-free output discretization of the weighted role allocation mechanism to three distinct values $\zeta = \{-1, 0, 1\}$ is achieved by an output quantization with hysteresis. The rate of change of the internal continuous policy parameter $\hat{\alpha}$ is also chosen depending on the agreement indicator ξ from Equation (4.20) with

$$\dot{\hat{\alpha}} = \begin{cases} \tau_{+,d}, & \text{if } \xi = 1 \\ \tau_{-,d}, & \text{otherwise.} \end{cases}$$

A quantization with hysteresis maps the internal continuous policy parameter $\hat{\alpha}$ onto the discrete value ζ, replacing the continuous output Equation (4.19). A smooth



(a) Weighted proactive role allocation.



(b) Discrete proactive role allocation.

Figure 4.7: Policy parameter α over time for a simulated human wrench profile $\tilde{u}^C_{1,y,m}$ and an expected wrench component $\tilde{u}^C_{1,y} > 0$.

transition between the three discrete levels is achieved by a bang-bang-like ramp generating mechanism

$$\dot{\alpha} = \tau_b \operatorname{sgn}(\zeta - \alpha),$$

where τ_b denotes a blending time constant. The behavior of the discrete role allocation scheme is also illustrated by simulation as in example in Figure 4.7(b).

4.3 Robot interaction control

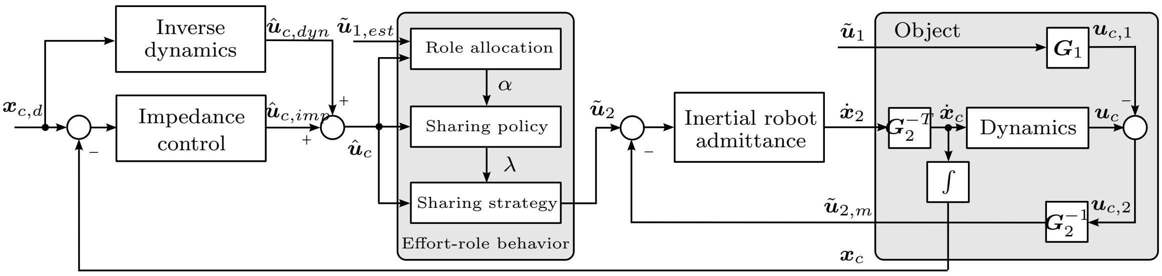


Figure 4.8: Overall interaction control architecture embedding the effort-role behavior.

In order to embed the role behavior developed in Section 4.2 into a robotic agent, we present an architecture for feedback interaction control as in Figure 4.8. The robot applies wrench $\tilde{\boldsymbol{u}}_2$ by an admittance-type force controller imposing motion at the robot's grasp point $\boldsymbol{x}_2$ on the object. The effort-role behavior module consists of three submodules, namely role allocation, sharing policy and sharing strategy; and generates the robot's input behavior for given external wrenches $\hat{\boldsymbol{u}}_c$ and estimates of the human applied wrench $\tilde{\boldsymbol{u}}_{1,est}$. An object-related trajectory $\boldsymbol{x}_{c,d}$ is provided as reference to the system's inverse dynamics comprising the model of the object as well as the robot, and generates a feedforward component of the external wrench $\hat{\boldsymbol{u}}_{c,dyn}$. The feedback component $\hat{\boldsymbol{u}}_{c,imp}$ is generated as output of an impedance control law, and ensures tracking of the object configuration under model uncertainties and unexpected human behavior.

4.3.1 Estimation of the partner's input

In this section, the interaction control architecture is explained in detail. The robotic agent is capable of computing an estimate of the applied wrench of a single human partner. If the robot's has sufficiently accurate kinesthetic feedback available through its end effector with a rigid grasp at $\boldsymbol{x}_2$, i.e. it provides measurements $(\boldsymbol{x}_2, \dot{\boldsymbol{x}}_2, \ddot{\boldsymbol{x}}_2)$ of the grasp point's configuration, the object's motion $(\boldsymbol{x}_c, \dot{\boldsymbol{x}}_c, \ddot{\boldsymbol{x}}_c)$ can be inferred using the robot's partial grasp matrix $\boldsymbol{G}_2^T$, which is invertible for a rigid grasp. In the dyadic case, the external wrench is superposed by the partners' wrench components according to Equation (4.3), c.f. $\boldsymbol{u}_c = \boldsymbol{u}_{c,1} + \boldsymbol{u}_{c,2}$ in Figure 4.8. Thus, we obtain the estimated applied wrench

$$\tilde{\boldsymbol{u}}_{1,est} = \boldsymbol{G}_1^{-1} \left(\boldsymbol{u}_c - \boldsymbol{G}_2 \tilde{\boldsymbol{u}}_{2,m}\right), \tag{4.21}$$

where the external wrench $\boldsymbol{u}_c$ is calculated using the inverse dynamics[3] in Equation (4.1), $\tilde{\boldsymbol{u}}_{2,m}$ is the measured applied wrench of the robot and $\boldsymbol{G}_1$ is the human's partial grasp matrix. Due to the superposition of external wrench components (Equation (4.3)), only a single agent's unknown input can be determined uniquely by Equation (4.21).

4.3.2 Admittance-type force control

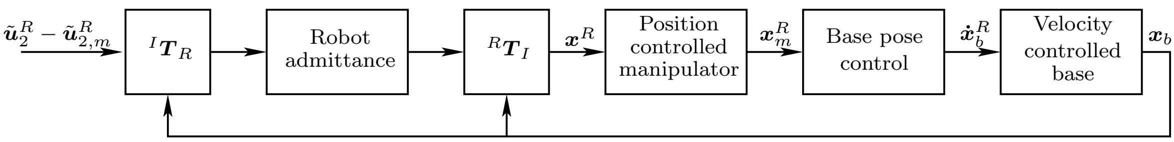


Figure 4.9: Inertial admittance-type control scheme including manipulator-base coordination.

An admittance-type force control law is utilized to impose the robot's applied wrench $\tilde{\boldsymbol{u}}_2$. The controller renders the dynamics

$$\boldsymbol{u}_2 - \boldsymbol{u}_{2,m} = \boldsymbol{M}_r \ddot{\boldsymbol{x}}_2 + \boldsymbol{D}_r \dot{\boldsymbol{x}}_2, \tag{4.22}$$

where $\boldsymbol{u}_{2,m}$ is the measured input wrench and matrices $\boldsymbol{M}_r$ and $\boldsymbol{D}_r$ are a rendered virtual robot's mass and friction respectively. Note that for a rigid grasp, Equation (4.22)

[3]Certain non-linearities such as static friction prevent invertibility of the object dynamics and therefore the partner's input estimation.

has to be formulated in $\dim(\boldsymbol{u}_2)$. Zeroing ineffective components of $\boldsymbol{u}_2$ (e.g. $\boldsymbol{u}_{2,\phi} = 0$) yields the robot's applied wrench $\tilde{\boldsymbol{u}}_2$. In order to make use of the extended workspace of a mobile robot composed by a manipulator-base system, the admittance control law is calculated in the inertial frame similar to Unterhinninghofen et al. (2008). The control scheme depicted in Figure 4.9 compensates for repositioning of the mobile base through transformations between the local robot frame R and the inertial frame, which are denoted by ${}^{I}\boldsymbol{T}_R$ and ${}^{R}\boldsymbol{T}_I$ respectively, so that the grasp pose of the manipulator is not affected.

Following of the mobile base is ensured by the velocity command

$$\dot{\boldsymbol{x}}_b^R = \begin{pmatrix} \dot{x}_{b,\phi} & \dot{x}_{b,x} & \dot{x}_{b,y} \end{pmatrix}^T$$

generated according to the control law

$$\dot{\boldsymbol{x}}_b^R = \operatorname{diag}\left(K_{hdg}, K_{dst}, K_{tng}\right) \begin{pmatrix} e_{hdg} & e_{dst} & e_{tng} \end{pmatrix}^T. \tag{4.23}$$

Three independent proportional controllers with gains K_{hdg}, K_{dst} and K_{tng} move the mobile base, minimizing heading error e_{hdg}, distance error e_{dst} and tangential error e_{tng} with respect to a desired relative configuration of the manipulated object and the robot base, as illustrated in Figure 4.10. The desired pose of the end-effector $\boldsymbol{x}_d^R$ w.r.t. the robot frame R is chosen to meet a certain lower bound μ_{min} of the manipulability measure

$$\sqrt{\det\left(\boldsymbol{J}^T\boldsymbol{J}\right)} > \mu_{min} \quad \forall\, \|\boldsymbol{x}_d^R - \boldsymbol{x}_m^R\| < \Delta\boldsymbol{x}^R,$$

where $\boldsymbol{J}$ is the Jacobian of the manipulator and $\Delta\boldsymbol{x}^R$ describes required workspace bounds during manipulation. Assuming a rigid grasp of the robot's manipulator on the object, the errors e_{hdg}, e_{dst} and e_{tng} can be determined as a function of $\boldsymbol{x}_d^R$ and $\boldsymbol{x}_m^R$. The control gains in Equation (4.23) are tuned to achieve a smoothly-damped, spring-like following behavior of the platform that keeps the manipulator within its workspace bounds during mobile manipulation. The resulting motion command $\dot{\boldsymbol{x}}_b^R$ is then executed by an omni-directional velocity control law as proposed in (Nitzsche et al., 2003).

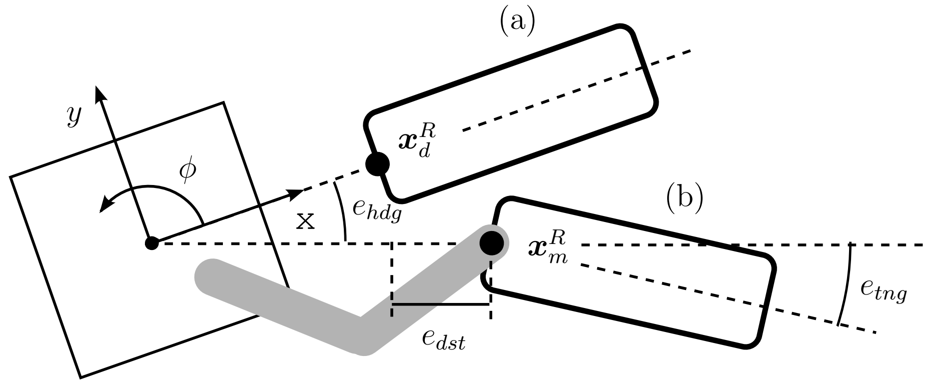


Figure 4.10: (a) Desired and (b) actual configuration of the base w.r.t. the object, described by a desired and measured pose of the manipulator's end-effector, $\boldsymbol{x}_d^R$ and $\boldsymbol{x}_m^R$ respectively.

4.3.3 Object-centered motion tracking

In addition to the capability of applying input wrenches $\tilde{\boldsymbol{u}}_2$ on the manipulated object, the mobile robotic agent needs the capability to impose a desired trajectory of the object configuration $\boldsymbol{x}_{c,d}$ as a result of the shared plan. The tracking behavior is synthesized in an object-centered representation by means of an external wrench

$$\hat{\boldsymbol{u}}_c = \hat{\boldsymbol{u}}_{c,dyn} + \hat{\boldsymbol{u}}_{c,imp}, \tag{4.24}$$

decomposed by the underlying effort-behavior. Wrench component $\hat{\boldsymbol{u}}_{c,dyn}$ compensates in a feedforward branch for the dynamics of the combined manipulator-object system with

$$\hat{\boldsymbol{u}}_{c,dyn} = \boldsymbol{M}(\boldsymbol{x}_c, \dot{\boldsymbol{x}}_{c,d})\ddot{\boldsymbol{x}}_{c,d} + \boldsymbol{f}(\boldsymbol{x}_c, \dot{\boldsymbol{x}}_{c,d}), \tag{4.25}$$

where mass matrix $\boldsymbol{M}(\boldsymbol{x}_c, \dot{\boldsymbol{x}}_{c,d})$ and friction term $\boldsymbol{f}(\boldsymbol{x}_c, \dot{\boldsymbol{x}}_{c,d})$ comprise the mass and friction terms from Equation (4.1) and Equation (4.22). An object-centered impedance-type control law acting on the tracking error of the configuration $\boldsymbol{x}_c$ generates the external wrench component

$$\hat{\boldsymbol{u}}_{c,imp} = \boldsymbol{K}_p(\boldsymbol{x}_{c,d} - \boldsymbol{x}_c) + \boldsymbol{K}_d(\dot{\boldsymbol{x}}_{c,d} - \dot{\boldsymbol{x}}_c). \tag{4.26}$$

Stiffness gain $\boldsymbol{K}_p$ and damping gain $\boldsymbol{K}_d$ render a compliant behavior, if the object configuration deviates from the expected.

The external wrench Equation (4.24), which guarantees object-centered motion tracking, feeds the effort-role behavior, and can be regarded as a selective wrench filter. Depending on the estimated human's applied wrench $\tilde{\boldsymbol{u}}_{1,est}$ and the policy parameter α, the robot's applied wrench $\tilde{\boldsymbol{u}}_2$ is calculated to reflect the amount of the robot's voluntary contribution to the task effort as a result of the effort-role behavior. The admittance-type force control law Equation (4.22) imposes the applied wrench on the object and renders the robot's input behavior.

4.4 Experiment

In order to evaluate our effort sharing strategy and the effects of the role allocation schemes developed in Section 4.2.5, we conducted a user study at Munich *Multi Joint Action Laboratory* of *CoTeSys* research center. A human-robot interaction scenario was designed for this study in a unique large-scale setup, involving the joint manipulation of a real-sized bulky object. The participants were asked to maneuver jointly with a human-sized mobile robot through our cluttered lab area (see Figure 4.1) in order to collaboratively transport a table. The realization of such a joint action task serves as the proof of concept for our approach and provides valuable observations through a real scenario. In this section, we describe the experimental setup, conditions, design, and the procedure.

4.4.1 Experimental setup

The mobile robot used in the experiment consists of an omni-directional mobile base developed by Hanebeck et al. (1999), two admittance-controlled anthropomorphic manipulators (Stanczyk and Buss, 2004) using 6-degrees-of-freedom wrench sensors (*JR3 67M25A3-I40-DH*) on each end effector. A two-finger parallel gripper of type *Schunk PG70*, which is mounted at the robot's right manipulator, provides a rigid grasp of the flange attached to the table. The flange is a solid wooden plate that provided slippage free zero-backlash grasp for the robot. A detailed description of the robot's system hardware and software architecture can be found in (Althoff et al., 2009; Medina et al., 2011). During the experiment all data collection is done by the mobile robot at a sampling frequency of 1 kHz. The wrench sensor at the human-side is identical to that attached to the end effector of the robot and it is connected to a PC on the robot. The table configuration as well as the grasp points are tracked using the robot's inverse kinematics, transformed by the mobile base's odometry readings. The interaction control architecture is implemented in *MATLAB Simulink* and executed at 1 kHz under *Ubuntu Linux* utilizing *Matlab's Real-Time Workshop.*

During the experiment, the subjects are asked to move a wooden table weighing 44 kg that is mounted on an aluminum frame standing on ball-caster feet (see Figure 4.1). The ball casters provide low-friction, holonomic maneuverability of the table. A handle and a flange are rigidly attached to the table at facing sides to serve as grasp points for the human and the robot, respectively (see Figure 4.11).

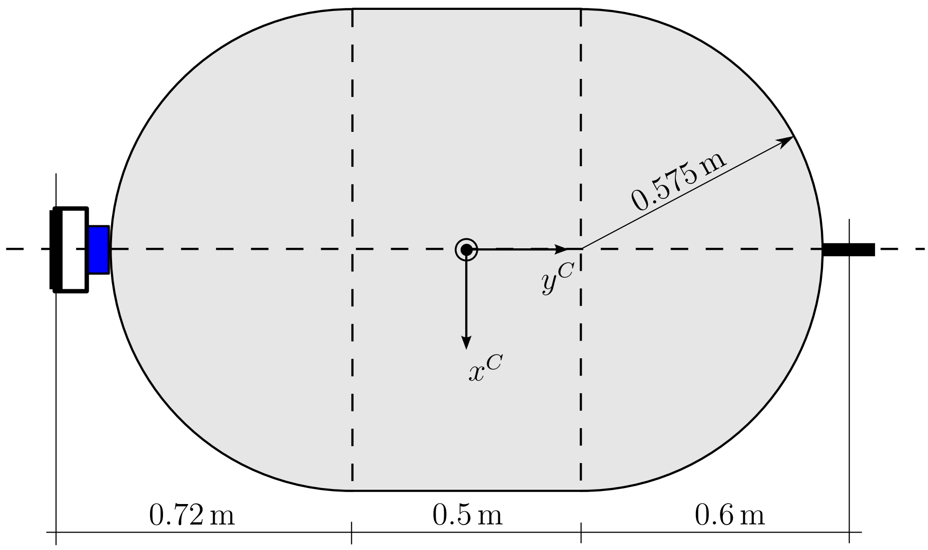


Figure 4.11: Cooperatively manipulated table equipped with a handle and wrench sensor for the human (left) and a grasp flange for the robot (right), both mounted at a height of 0.925 m over the ground.

The parameters used by the robot's interaction control architecture Equation (4.22) and Equation (4.26) in Section 4.3 are set to the following values regarding the task-relevant degrees of freedom:

$$\begin{aligned}
\boldsymbol{M}_r &= \mathrm{diag}(0.4\,\mathrm{kgm}^2, 20\,\mathrm{kg}, 20\,\mathrm{kg}) \\
\boldsymbol{D}_r &= \mathrm{diag}(10\,\mathrm{Nmsrad}^{-1}, 100\,\mathrm{Nsm}^{-1}, 100\,\mathrm{Nsm}^{-1}) \\
\boldsymbol{K}_p &= \mathrm{diag}(200\,\mathrm{Nrad}^{-1}, 200\,\mathrm{Nm}^{-1}, 200\,\mathrm{Nm}^{-1}) \\
\boldsymbol{K}_d &= \mathrm{diag}(50\,\mathrm{Nmsrad}^{-1}, 50\,\mathrm{Nsm}^{-1}, 50\,\mathrm{Nsm}^{-1})
\end{aligned}$$

An off-line estimation of the object dynamics used in Equation (4.25) revealed the parameters of the table mass matrix

$$\boldsymbol{M}_c = \mathrm{diag}(13.5\,\mathrm{kgm}^2, 44\,\mathrm{kg}, 44\,\mathrm{kg}).$$

The table friction $\boldsymbol{f}_c$ is considered as a Coulomb-type friction of 14 N in total, acting at the table feet.

4.4.2 Conditions

We designed three conditions implementing different behaviors for the robot:

1. *Constant Role Allocation (CRA):* As explained in Section 4.2.5, the robot contributes to the task without changing its role, i.e. it uses a balanced-effort policy $\alpha = 0$ at all times.

2. *Weighted Proactive Role Allocation (WPRA):* As explained in Section 4.2.5, as long as the force applied by the human is in the expected direction, or the human is inactive, the robot increases the policy parameter α gradually with time. Otherwise, it decreases α. During the experiment, we used $\tau_{+,w} = 0.02\,(\mathrm{Ns})^{-1}$, $\tau_{-,w} = -0.04\,(\mathrm{Ns})^{-1}$, and $\tilde{u}^C_{1,y,thr} = 10\,\mathrm{N}$.

3. *Discrete Proactive Role Allocation (DPRA):* Similar to WPRA, the robot changes its role by gradually increasing or decreasing α. We defined three discrete roles

in this condition (see Section 4.2.5). During the experiment, we used $\tau_{+,d} = 0.2\,\mathrm{s}^{-1}$, $\tau_{-,d} = -2\,\mathrm{s}^{-1}$, and $\tau_b = 2\,\mathrm{s}^{-1}$.

4.4.3 Participants, procedure and design

18 subjects (6 female and 12 male), aged between 19 and 44, participated in our study. All the subjects were right handed and used their right hands for moving the table. We conducted a within subjects experiment, in which each subject experimented with all conditions in a single day. The conditions (CRA, WPRA, and DPRA) were presented to the subjects in permuted order using a balanced Latin Square design to avoid learning effects. The subjects were given detailed instructions about the task and the conditions before the experiment.

In the experiment, a trial consisted of moving the table jointly with the robot to four parking configurations and then coming back to the initial configuration, as shown in Figure 4.12. The subjects were allowed to apply pushing and pulling forces using only their dominant hands by holding the handle on the table. However, lifting the table off the ground and talking during the experiment were prohibited. The positions of the human and the robot in each of the parking configurations were clearly marked on the floor of the area. These marks were shown to the subjects before the experiment. The free space available for maneuvering the table between the parking configurations was constrained by obstacles in such a way that ambiguities and possible alternative common paths were avoided.

For each condition, the subjects performed the task three times (i.e. three trials). After each trial, a small break was given to initialize the table and robot pose. After performing these three trials successfully, the subjects were given a questionnaire to comment on their experience. Afterwards, they were presented with a new condition.

4.5 Evaluation

In this section, quantitative as well as subjective measures used to evaluate the user experience are introduced.

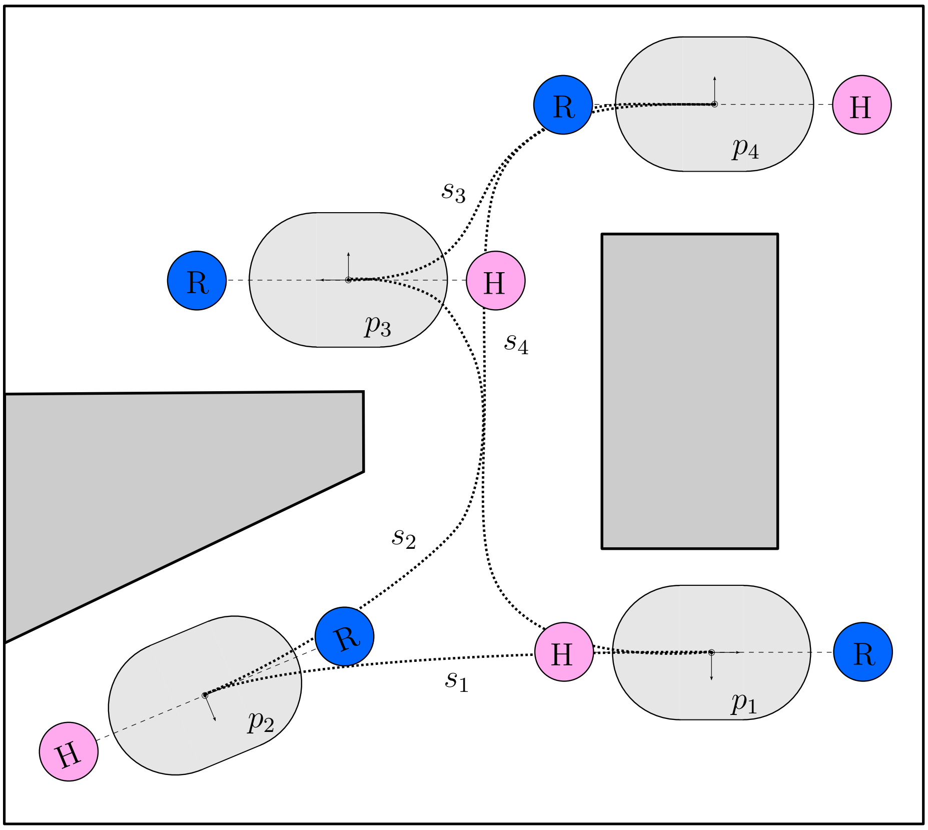


Figure 4.12: Bird's eye view of the lab area used for the experiments. The outer box corresponds to the boundary of the environment and spans a square of approximately $8\,\mathrm{m} \times 8\,\mathrm{m}$. The regions marked as gray are occupied by obstacles. The positions of the table and the interacting dyad (i.e. the human and the robot) in each of four designated parking configurations, $p_i, i = 1..4$, are depicted. The paths, $s_i, i = 1..4$, connecting the parking configurations are represented by dotted lines.

4.5.1 Quantitative measures

This section presents details on the quantitative measures we adopt in analysis. The data collected in the first 300 ms of each trial is discarded to eliminate possible discrepancies encountered at the beginning of the trials. Also data collected at the final leg of segment s_4 (see Figure 4.12) is discarded since the final parking procedure was difficult for some of the participants, and we had to cut some trials early due to impending collisions with obstacles. The data is low-pass filtered using a first-order filter with 15 Hz cut-off frequency.

Task performance is quantified in terms of task completion time. We also examine the individual interaction forces applied by the agents, the work done by the partners, and the total work done on the table as an indication of the physical effort. Also, the degree of cooperation under each condition is investigated with respect to the amount of disagreement in the dyad's operation and the distribution of the robot's effort policy.

Task performance

The completion time (CT) of each trial is taken as a measure of performance.

Effort

The average of the human's and robot's applied wrenches and the work done by them are considered to be indications of the *effort* made by the agents. Work done by the agents during a trial is calculated by

$$W_i = \int_0^{CT} |\tilde{\boldsymbol{u}}_{i,m} \cdot \dot{\boldsymbol{x}}_i| \, dt,$$

where $\tilde{\boldsymbol{u}}_{i,m}$ denotes the measured wrench exerted by the agent and $\dot{\boldsymbol{x}}_i$ the velocity of the grasp point. The total work done on the table by the partners during a trial considers the accumulated energy transfer on the table, i.e. how efficiently the table could be moved to the parking configurations. It is calculated by

$$W_{table} = \int_0^{CT} |\boldsymbol{u}_c \cdot \dot{\boldsymbol{x}}_c| \, dt,$$

where the motion-causing external wrench $\boldsymbol{u}_c$ is obtained by evaluating Equation (4.3) for $\tilde{\boldsymbol{u}}_{i,m}$. Note that the absolute energy flow is accumulated, since the human partner is assumed not to recoup by absorbing energy, i.e. through breaking actions.

Amount of disagreement

In our experiment, a disagreement is assumed to occur when two partners pull or push the table in opposite directions along the y^C-axis. Instead of contributing to the movement of the object, part of the forces in this axis are wasted for compressing the table (i.e. squeeze force) or resisting the other partner (i.e. tensile force). Groten et al. (2009) call these forces interactive forces. The interaction force at a given time is defined as

$$u_I = \begin{cases} \tilde{u}^C_{1,y}, & \text{if } \operatorname{sgn}(\tilde{u}^C_{1,y}) \neq \operatorname{sgn}(\tilde{u}^C_{2,y}) \\ & \wedge\ |\tilde{u}^C_{1,y}| \leq |\tilde{u}^C_{2,y}| \\ -\tilde{u}^C_{2,y}, & \text{if } \operatorname{sgn}(\tilde{u}^C_{1,y}) \neq \operatorname{sgn}(\tilde{u}^C_{2,y}) \\ & \wedge\ |\tilde{u}^C_{1,y}| > |\tilde{u}^C_{2,y}| \\ 0, & \text{otherwise.} \end{cases}$$

In order to come up with a metric of disagreement, the interactive forces during the disagreement periods are weighed with the time spent in disagreement. Since we are not interested whether the agents disagree by pushing or pulling against each other (which is indicated by sign of u_I), the *amount of disagreement*

$$ADI = \int_0^{CT} |u_I| \, dt,$$

is calculated based on the magnitude of the interactive forces.

Role allocation

The *frequency distribution* of the policy parameter α is investigated to provide a better understanding of the dynamic role allocation behaviors in different conditions.

4.5.2 Subjective measures

At the end of each condition, the subjects are asked to fill in a questionnaire, the contents of which is available in Appendix C.3. The questionnaire consists of 20 questions, 6 of which are taken from NASA-TLX task load index (Hart and Stavenland, 1988), and 14 of which are adopted from Kucukyilmaz et al. (2013). The subjects indicate their level of agreement or disagreement on a 7-point Likert scale for a series of questions, some of which are rephrased and asked again within the questionnaire in an arbitrary order. The average of the subjects' responses to the rephrased questions is used for the evaluation.

NASA-TLX evaluates the degree to which each of the following six factors contribute to the task workload:

- *Mental Demand:* One question asks how much mental and perceptual activity was required for achieving the task (e.g. thinking, deciding, calculating, remembering, looking, searching, etc.).

- *Physical Demand:* One question asks how much physical activity was required for achieving the task (e.g. pulling, pushing, turning, calculating, remembering, looking, searching, etc.).

- *Temporal Demand:* One question asks how much time pressure the subjects felt during the task.

- *Performance:* One question asks the subjects to assess their self-performance in accomplishing the goals of the task.

- *Effort:* One question asks how hard the subjects had to work to accomplish their level of performance.

- *Frustration Level:* One question asks how much irritation, stress or annoyance the subjects felt during the task.

The remaining questions are asked in the following categories:

- *Collaboration:* Two questions investigate the extent to which the subjects had a sense of collaborating with the robot during the task.

- *Interaction:* Two questions explore the level of interaction the subjects experience during the task.

- *Comfort:* One question asks how comfortable the task was.

- *Pleasure:* One question asks how pleasurable the task was.

- *Degree of Control:* Two questions ask the subjects about their perceived degree of control on the movement of the table.

- *Predictability:* Two questions investigate how predictable the robot's movements were during the task.

- *Trust:* Two questions investigate whether the subjects trusted their robotic partner on controlling the table or not.

- *Human-likeness:* Two questions ask the subjects whether the robot's actions (movement patterns) resembled those of a human being acting in a similar real-life scenario.

4.6 Results

This section presents the results of the experiment in terms of the quantitative and subjective measures defined in Section 4.5. Statistically significant differences between conditions are investigated using one-way repeated measures ANOVA and multiple comparisons are performed via post-hoc t-tests with Bonferroni correction. Mauchly's test is conducted to check if the assumption of sphericity was violated. If so, the degrees of freedom are corrected using Huynh-Feldt estimates of sphericity.

4.6.1 Quantitative analysis

In this section, we present the quantitative results according to the measures introduced in Section 4.5.1.

Task performance

Figure 4.13 illustrates the mean completion time under each condition and the standard error of the means. The conditions are ranked in ascending order of mean completion time as WPRA, DPRA, and CRA. This implies that proactive role allocation is especially beneficial for improving the completion time when implemented in a weighted fashion (WPRA).

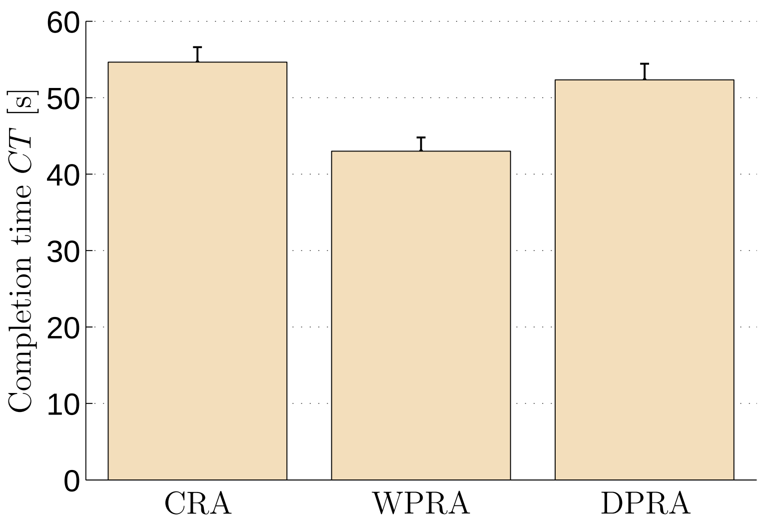


Figure 4.13: Average completion time of the task. The bars represent standard errors of the means.

Tables 4.1 and 4.2 present ANOVA results and the p-values for the multiple comparisons between conditions. Mauchly's test indicates that the assumption of sphericity is violated for completion time ($\chi^2(2) = 7.32$, $p < 0.05$), therefore the degrees of freedom are corrected using Huynh-Feldt estimates of sphericity ($\epsilon = 0.91$). According to ANOVA results, we observe a statistically significant effect of the condition on completion time ($p < 0.001$). Specifically, the subjects completed the task significantly faster under WPRA than they did under the other two conditions. While the completion time is slightly smaller in DPRA than it is in CRA, the difference between these conditions is not significant.

Source	Type III SS	df	MS	F	p
CT	4.10×10^9	1.82	2.25×10^9	15.76	.000
Error	1.38×10^{10}	96.69	1.43×10^8		

Table 4.1: ANOVA results for task completion time

	p-values		
	CRA-WPRA	CRA-DPRA	WPRA-DPRA
CT	.000(*)	1.000	.000(*)
* The mean difference is significant at p = .05 level.			

Table 4.2: The pairwise comparison of the conditions for task completion time

Effort

Figure 4.14 illustrates the mean individual wrenches applied by the agents and the standard error of the means. The average applied wrench at the human's side is lowest for WPRA, followed by CRA and DPRA. On the other hand, for the robot, the average applied wrench is lowest for CRA, followed by WPRA and DPRA.

Tables 4.3 and 4.4 present ANOVA results and the p-values for the multiple comparisons between conditions for individual wrenches applied by the agents. Mauchly's test indicates that the assumption of sphericity is violated for the wrenches applied by the human ($\chi^2(2) = 18.92$, $p < 0.05$, $\epsilon = 0.79$) and the robot ($\chi^2(2) = 10.33$,

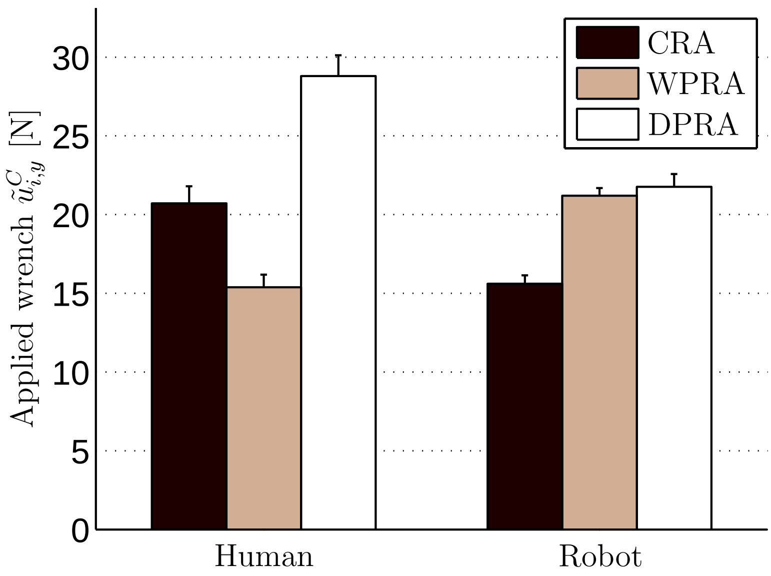


Figure 4.14: Average applied wrenches of the human and the robot. The bars represent standard errors of the means.

Source	Type III SS	df	MS	F	p
$\tilde{u}^C_{1,y}$ (Human)	4.93×10^3	1.57	3.14×10^3	71.56	.000
Error	3.65×10^3	83.17	43.92		
$\tilde{u}^C_{2,y}$ (Robot)	1.25×10^3	1.75	7.16×10^2	50.32	.000
Error	1.32×10^3	92.46	14.22		

Table 4.3: ANOVA results for the individual forces applied by the agents

$p < 0.05$, $\epsilon = 0.87$), therefore the degrees of freedom are corrected using Huynh-Feldt estimates of sphericity.

According to ANOVA results, the experimental condition has a significant effect on individual wrenches for both the human and the robot ($p < 0.001$). We observe that the average wrench applied by the human under WPRA is significantly smaller than it is under the other conditions ($p < 0.001$), whereas it is significantly higher under DPRA ($p < 0.001$). The applied wrench of the robot is significantly higher under WPRA and DPRA than it is under CRA ($p < 0.001$).

	p-values		
	CRA-WPRA	CRA-DPRA	WPRA-DPRA
$\tilde{u}^C_{1,y}$ (Human)	.000(*)	.000(*)	.000(*)
$\tilde{u}^C_{2,y}$ (Robot)	.000(*)	.000(*)	1.000
* The mean difference is significant at p = .05 level.			

Table 4.4: The pairwise comparison of the conditions individual forces applied by the agents

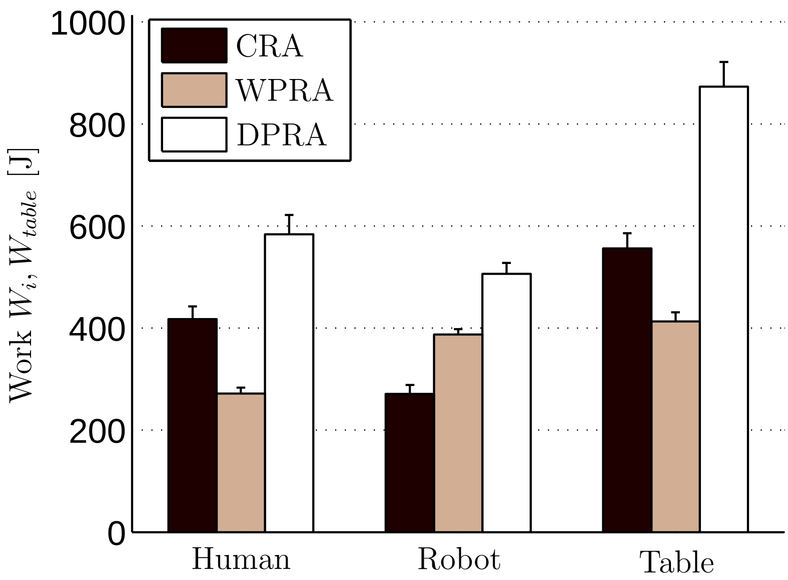


Figure 4.15: Average work done by individual agents and average work done on the table. The bars represent standard errors of the means.

Figure 4.15 illustrates the average work done by the individual agents and the dyad under each condition. The error bars denote the standard error of the means. The results are in parallel to those observed for the wrenches applied by the agents:

The work done by the human and the total work done by the dyad is lowest in WPRA, followed by CRA and DPRA. The robot's work done is the lowest in CRA, followed by WPRA and DPRA.

Tables 4.5 and 4.6 present ANOVA results and the p-values for the multiple comparisons between conditions in terms of work. Mauchly's test indicates that the assumption of sphericity is violated for work done by the human ($\chi^2(2) = 22.76$, $p < 0.05$, $\epsilon = 0.754$), the robot ($\chi^2(2) = 14.81$, $p < 0.05$, $\epsilon = 0.82$), and the dyad ($\chi^2(2) = 19.35$, $p < 0.05$, $\epsilon = 0.78$), therefore the degrees of freedom are corrected using Huynh-Feldt estimates of sphericity.

Source	Type III SS	df	MS	F	p
W_1 (Human)	2.20×10^6	1.51	1.46×10^6	62.14	.000
Error	1.87×10^6	79.96	2.34×10^4		
W_2 (Robot)	6.12×10^5	1.65	3.72×10^5	47.41	.000
Error	6.85×10^5	87.19	7.85×10^3		
W_{Table}	4.03×10^6	1.56	2.58×10^4	44.09	.000
Error	4.85×10^6	82.78	5.86×10^4		

Table 4.5: ANOVA results for the work done by individual agents and the dyad

We consider the work done as an indication of physical effort. ANOVA results suggest that there is a significant effect of the experimental condition on the individual work done by the agents and the work done on the table ($p < 0.001$). We observe that the subjects put the least effort under WPRA ($p < 0.001$) and the most under DPRA ($p < 0.001$). Similarly, we observe that the total work done on the table under WPRA is smaller than that under CRA ($p < 0.05$) and DPRA ($p < 0.001$). The total work is the largest under DPRA ($p < 0.001$). The robot showed significantly more effort under WPRA and DPRA than it did under CRA ($p < 0.001$). Even though we observe the highest robot effort in DPRA, the difference between the

	p-values		
	CRA-WPRA	CRA-DPRA	WPRA-DPRA
W_1 (Human)	.000(*)	.000(*)	.000(*)
W_2 (Robot)	.000(*)	.000(*)	.520
W_{Table}	.026(*)	.000(*)	.000(*)
* The mean difference is significant at p = .05 level.			

Table 4.6: The pairwise comparison of the conditions for the work done by individual agents and the dyad

WPRA and DPRA conditions is not statistically significant.

Amount of disagreement

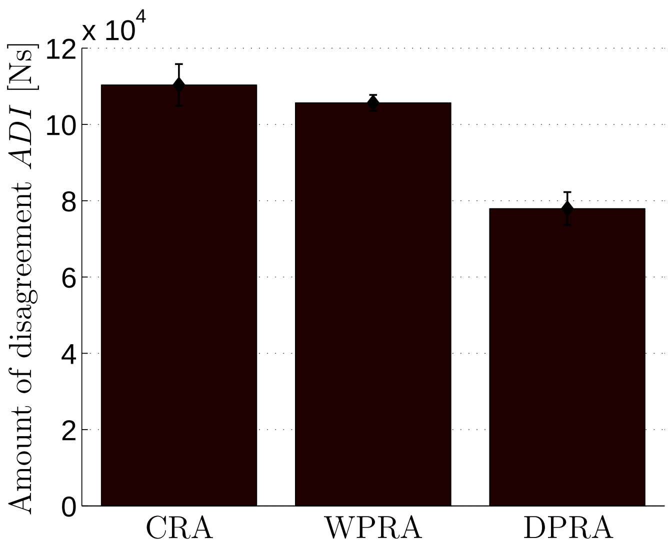


Figure 4.16: The averaged amount of disagreement under each condition. The bars represent standard errors of the means.

The amount of disagreement under each condition is illustrated in Figure 4.16. ANOVA results and the p-values for the multiple comparisons between conditions for the amount of disagreement are listed in Tables 4.7 and 4.8. Mauchly's test indicates that the assumption of sphericity is violated ($\chi^2(2) = 0.86$, $p < 0.05$, $\epsilon = 0.90$), hence the degrees of freedom were corrected using Huynh-Feldt estimates of sphericity.

Source	Type III SS	df	MS	F	p
ADI	3.32×10^{10}	1.80	1.84×10^{10}	21.14	.000
Error	8.32×10^{10}	95.48	8.71×10^{8}		

Table 4.7: ANOVA results for the amount of disagreement

	p-values		
	CRA-WPRA	CRA-DPRA	WPRA-DPRA
ADI	1.000	.000(*)	.000(*)
* The mean difference is significant at p = .05 level.			

Table 4.8: The pairwise comparison of the conditions for the amount of disagreement

The ANOVA results indicate a significant effect of the condition on the amount of disagreement ($p < 0.05$). The multiple comparison results imply that the amount of disagreement is similar under CRA and WPRA, whereas it is lower under DPRA than CRA ($p < 0.001$) and WPRA ($p < 0.001$). Note that we consider only the signs of the applied wrenches to decide whether there is a disagreement between the partners. Also we check for interactive forces that are smaller than 1 N, and do not treat these as disagreements.

Role allocation

Figure 4.17 illustrates how the role allocation behavior changes for the WPRA and DPRA conditions. For each condition, a sample trial is selected showing the human's wrench profile and the resulting profile of the policy parameter α. Upon examining the

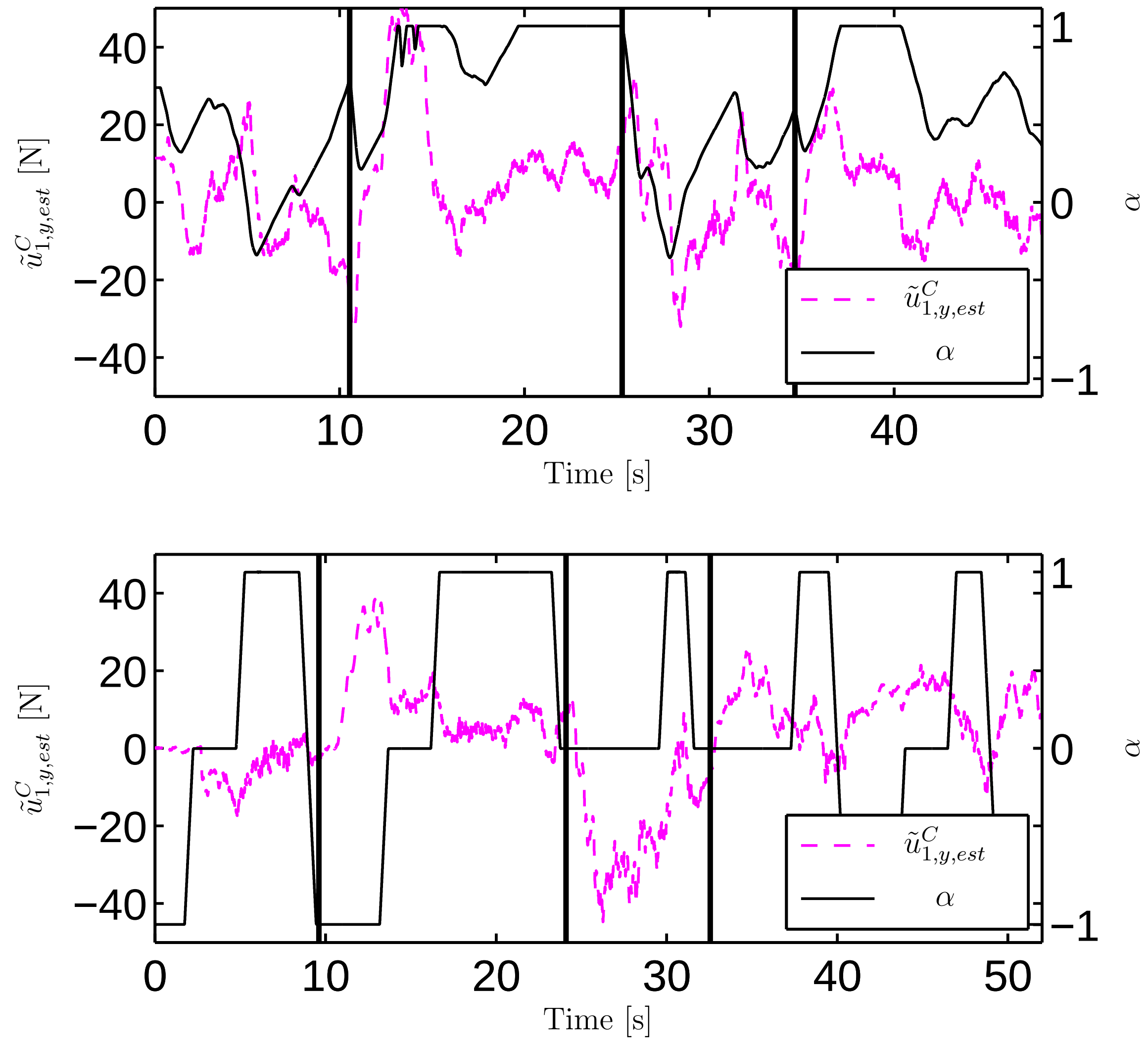


Figure 4.17: Sample trials for conditions WPRA (top) and DPRA (bottom). The straight lines denote the policy parameter α, and the dashed lines denote the component $\tilde{u}^C_{1,y,est}$ of the human's wrench profile. Task segments are separated by vertical bold lines.

plots, we observe that even though the human's wrench profile is similar under WPRA and DPRA, the resulting robot behavior is drastically different. In particular, the discrete state transitions under DPRA become obvious in contrast to the continuous blending under WPRA.

The frequency distributions of the policy parameter α under the WPRA and DPRA conditions are illustrated in Figure 4.18. In this experiment, we observe that under WPRA, the robot acts towards maximum effort. On the other hand, under DPRA, we see an almost uniform distribution between the three discrete states of effort sharing behaviors (due to transitions, we also notice values in between these three states).

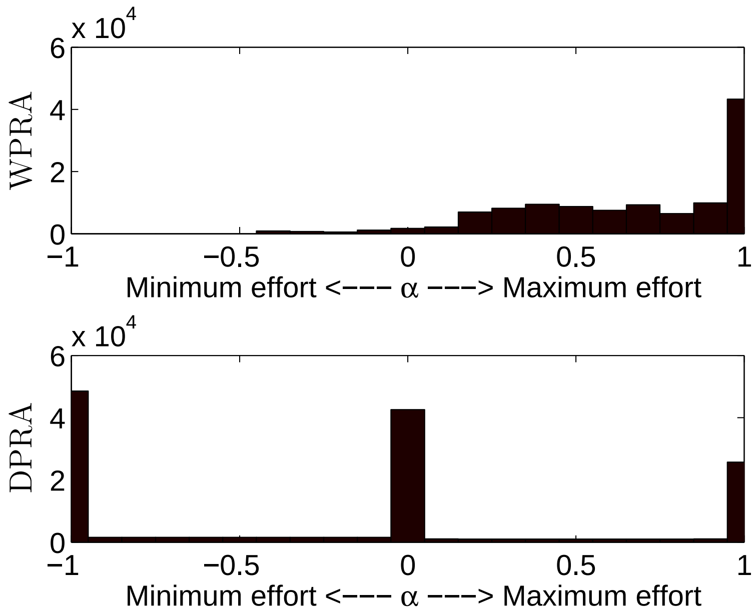


Figure 4.18: The frequency distribution of the policy parameter α under each condition.

4.6.2 Subjective evaluation

Figure 4.19 shows the mean values of the subjects' responses to the questionnaire and the standard error of the means.

The key results of the subjective evaluation are as follows:

- The subjects thought that the task was physically and mentally less demanding

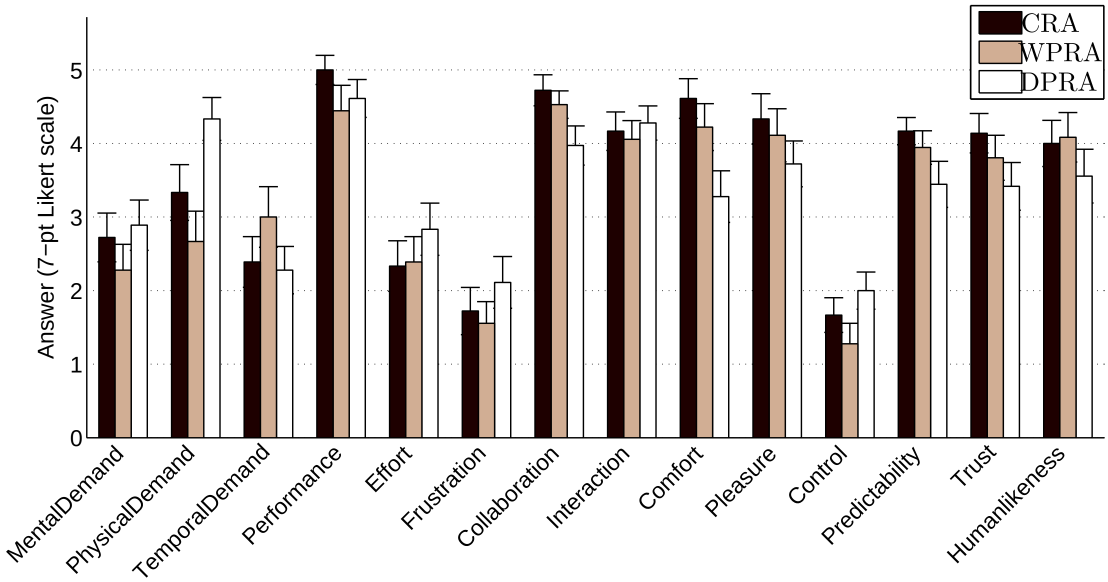


Figure 4.19: Means of the subjective measures in each condition. The bars represent standard errors of the means.

under WPRA. The physical demand for DPRA was significantly higher than it was for WPRA ($p < 0.005$) and CRA ($p < 0.05$).

- The subjects felt significantly less comfortable under DPRA than they felt under CRA ($p < 0.01$) and WPRA ($p < 0.005$).

- The subjects believed that their control over the table's movements under DPRA was significantly more than that under WPRA ($p < 0.05$).

- Under DPRA, the predictability of the robot was significantly lower than it was under CRA ($p < 0.05$).

Tables 4.9 and 4.10 present the ANOVA results and the p-values for multiple comparisons between conditions.

Source	Type III SS	df	MS	F	p
Mental Demand	3.593	2	1.796	2.809	.074
Physical Demand	25.333	2	12.667	9.229	.001
Temporal Demand	5.444	2	2.722	3.400	0.045
Performance	2.926	2	1.463	3.452	.043
Effort	2.704	2	1.352	1.644	.208
Frustration Level	2.926	2	1.463	1.474	.243
Collaboration	5.454	2	2.727	4.082	.026
Interaction	.444	2	.222	.306	.739
Comfort	16.926	2	8.463	7.492	.002
Pleasure	3.444	2	1.722	1.398	.261
Degree of Control	4.704	2	2.352	3.060	.060
Predictability	4.926	2	2.463	3.603	.038
Trust	4.704	2	2.352	2.343	.111
Human-likeness	2.898	2	1.449	1.543	.228

Table 4.9: ANOVA results for the subjective measures.

	p-values		
	CRA-WPRA	CRA-DPRA	WPRA-DPRA
Mental Demand	.447	1.000	.089
Physical Demand	.526	.013(*)	.001(*)
Temporal Demand	.231	1.000	.148
Performance	.168	.147	1.000
Effort	1.000	.430	.489
Frustration Level	1.000	.963	.348
Collaboration	1.000	.066	.168
Interaction	1.000	1.000	1.000
Comfort	.896	.007(*)	.031(*)
Pleasure	1.000	.306	.699
Degree of control	.688	.906	.028(*)
Predictability	1.000	.050(*)	.323
Trust	1.000	.131	.784
Human-likeness	1.000	.698	.407
* The mean difference is significant at p = .05 level.			

Table 4.10: The pairwise comparison of the conditions for the subjective measures.

4.7 Discussion

In this study, we investigate the benefits of using a dynamic role allocation scheme for cooperative human-robot interaction. We implemented two different dynamic role allocation schemes, i.e. WPRA and DPRA, and compared them to a scheme with constant role allocation, i.e. CRA. The evaluation of cooperative physical human-robot interaction is especially tricky due to the diversity of real life applications and target domains. In such systems, optimizing for the human's collaborative experience as well as the task performance is desired. In order to present a broad analysis, we utilize quantitative and subjective measures as explained in Section 4.5, each of which is designed to evaluate a different aspect of the cooperative task. Along with performance measures, we propose quantitative measures for evaluating the performance, effort, and efficiency of the partners in the dyadic task. Subjective measures are presented to discover the acceptability of the proposed schemes by the humans. However, our results indicate that no single interaction scheme can satisfy every aspect of interaction. Hence, the domain and task knowledge should be considered carefully.

The subjective evaluation, when considered along with the quantitative results presents insight about the users' perception of different effort sharing policies. During the experiments, we observed that, under DPRA, the subjects instantly accelerate and decelerate from time to time as an effect of adaptation to the changing policy α. We infer that such movements might be the reason why the subjects finish the task in a longer time. The average wrench of the robot is significantly higher under WPRA and DPRA than it is under CRA, which indicates a possible tendency towards maximum effort in the robot's behavior under both conditions. As a consequence of the smooth blending behavior under WPRA, the maximum effort policy that is dominantly employed by the robot makes the subjects think that the task requires them to be faster (i.e. the task has a higher temporal demand). Eventually this perception can be responsible for the lower completion time under WPRA.

We observe that the level of agreement during the task is the highest under DPRA. Reed et al. (2005) mention that sometimes force oscillations may be observed during interaction for negotiation purposes or in an effort to adapt to the varying velocity enforced by the robot. Since the states are discrete under DPRA, the behavior of the robot is observable. Hence, it is possible that the users use force oscillations less for adaptation purposes, but apply more consistent forces, resulting in an increased level of agreement during the task.

Under DPRA, the subjects are able to observe the operation of the robot more clearly and infer that different behaviors were displayed by the robot. On the other hand, WPRA results in a smoother role blending behavior, which is not consciously perceived by the subjects for the most of the time. We also observe that the mental and physical demand of task, as well as the frustration level and the physical effort are higher under DPRA. This may be an artifact of the pronounced role switching behavior faced during the task under DPRA.

The subjects think that the robot acts less collaboratively under WPRA and DPRA. A possible reason for this is that the changing behavior of the robot makes the interaction more complex, and the subjects favor a constant role allocation scheme. The subjects find the level of interaction to be higher under DPRA. Under WPRA, the role exchanges are probably too smooth to be observable, hence the subjects fail to perceive the interactive nature of the task.

The subjects feel in control of moving the table under DPRA significantly more than they do under WPRA. They also think that they spend more effort in DPRA, which agrees with our effort measures. Also, the drop in the perception of the relative control level of the subjects may be due to the greater effort that the robot displays under WPRA. Additionally, the subjects feel significantly less comfortable under DPRA and they think that the predictability of the robot is significantly lower than it is under CRA. Since the behavior of the robot is less smooth under DPRA, the subjects might feel discomfort due to abrupt role transitions and experience a difficult time in inferring the robot's actions in advance. However, in WPRA, as the behavior is smooth, the subjects are able to predict the robot's actions better. As the subjects are not able to infer the actions of the robot clearly under DPRA, they may be driven to being more dominant in pulling and pushing the table, which eventually increases their perceived control level during the task.

The subjects' belief that the robot would perform the task correctly is the highest under CRA, in which the subjects observe no unexpected behaviors as the robot's effort sharing policy is constant at all times. Finally, the humanlikeness of the robot is lower under DPRA than it is under WPRA and CRA. As mentioned above, we observe that the smooth operation under CRA and WPRA provides a more comfortable experience for the subjects, in which the subjects report that they could trust the robot and predict its actions. Even though we have not yet discovered the salient features that make the communication with a robot more humanlike, obviously subjective sensations such as smoothness, comfort, predictability, and trust adds to higher human-likeness scores.

Chapter 5

CONCLUSION

This dissertation presents the results of three experimental studies on the utility of a role exchange (RE) -or a role allocation (RA)- mechanism as a dynamic and personalized framework for human-robot collaboration. In this framework, a human dynamically interacts with a robot by communicating through the haptic channel to trade control levels on the task. In physical cooperation tasks, humans dominantly communicate over force information for negotiation purposes. Hence, our efforts aim at building robotic partners that can recognize and respond to the force signals acquired from humans during physical interaction.

Our results indicate a clear benefit of defining variable roles for partners and implementing a dynamic role exchange mechanism in dyadic human-robot interaction. The applicability of the proposed scheme to both virtual and physical scenarios is shown through controlled user studies in Chapters 3 and 4. Our findings indicate that a dynamic role exchange mechanism has measurable benefits over static control sharing schemes.

The evaluation of cooperative physical human-robot interaction is especially tricky due to the diversity of real life applications and target domains. In such systems, optimizing for the human's collaborative experience as well as task performance is desired. In order to present a broad analysis, we utilized quantitative and subjective measures as explained in Sections 3.3.3, 3.4.5 and 4.5, each of which is designed to evaluate a different aspect of the cooperative task. Along with spatial and temporal performance measures, we propose measures for evaluating the effort and efficiency of the partners in a dyadic task. Subjective measures are presented to discover the acceptability of the proposed schemes by the humans (see Appendices C.1 to C.3).

In our earlier studies (Oguz et al., 2010), we sought the benefits of the role exchange (RE) mechanism in comparison to an equal control (EC) guidance scheme. We hypothesized that the more transparent the REs, the more fluent the interaction. Hence, we did not inform the users of the system about the existence of the RE mechanism when performing a controlled user study. Even though the results of this user study indicate that the RE mechanism is not useful for improving task performance, yet is effective for optimizing the energy requirements of the human. In this sense, it presents the users with an option to choose and optimize between accuracy and energy. However, as a result of post-experiment interviews we realized that the some of the users were not able to use the mechanism, hence could not benefit from the system at its full capacity.

In order to address this issue, we designed an application, which requires users to perform REs more often (Kucukyilmaz et al., 2011, 2012, 2013). In a controlled user study, we explained the usage of the RE mechanism to the users first and then evaluated their performance. Our results suggest that the proposed RE mechanism improves task performance when compared to an equal control guidance scheme (EC). Hence, we infer that knowing about the underlying mechanism is indeed essential to get maximum benefit of robotic assistance. Also, we observed that the efficiency of the users and the joint efficiency of the dyad are significantly higher under RE condition. This implies that the users accomplish a higher amount of work with less effort when they are capable of exchanging roles with the robot. In contrast to Oguz et al. (2010), this result shows that the users can effectively benefit from a role exchange mechanism when they are explicitly instructed on the principles of interacting with the robot.

Additionally, we implemented certain sensory cues on top of the RE mechanism in order to make the role exchanges as visible to the user as possible (Kucukyilmaz et al., 2011, 2012, 2013). After a few pilot studies, we supplemented the system with additional visual and vibrotactile cues to inform the users on the control state regarding the negotiation process. The results of the user study indicate that the use of these visual and haptic cues (VHC) introduces an extra cognitive load to the users, which manifests itself in the form of performance deterioration. However, subjectively, these cues are useful in a sense that they make the interface of the system easier to use, the task more interactive, and allows users to trust their robotic partner more. Finally, we observe that the additional cues are helpful in conveying the control state to the users.

The knowledge acquired from the human studies conducted in virtual worlds is directly extensible to physical human-robot interaction. We showed the usability of the proposed role exchange mechanism to enhance the assistive capability of a robotic partner in physical cooperation with humans in (Moertl et al., 2012). In a controlled user study, we investigated two different methods for enabling dynamic role allocation (RA) in physical human-robot interaction. The first method, namely discrete proactive role allocation (DPRA), implements a step-like behavior for changing the role of the robot. This behavior uses three extreme behaviors for the robot and is highly visible to the users. The second method, namely weighted proactive role allocation (WPRA), implements REs in a smoother fashion, hence is more transparent. We compared the utility of WPRA and DPRA with a constrant role allocation (CRA) scheme.

The results of this user study draw a clear distinction between two different implementations of a the dynamic role allocation scheme. In comparison with WPRA, DPRA realizes more distinctive role transitions. This increases the visibility of the RE scheme by allowing the users to observe it clearly. This makes a DPRA-like scheme a viable alternative for interactive training applications. In training, it is necessary for the users to observe the role of the trainer (i.e. the robot) so that they can adapt to it. When the trainer's role is not perceived, the users typically tend to obey the guiding system and do not learn the dynamics of the system (Forsyth and MacLean, 2006). This effect can clearly be observed when we examine the frequency distribution of the policy parameter in Figure 4.18. As indicated in Section 4.6, under WPRA, the users tend to go along under the supervision of the robot most of the time. Since the robot puts its maximum effort into the task most of the time, the users would only seldom take initiative and hence fail to gain training experience. On the other hand, in many applications, users would prefer comfort over having a better sense of interaction. For instance, when working with an assistive robot in a cooperative manipulation task, users would prefer to finish the task in the fastest and the least tiring way. In such a setting, WPRA would be the better alternative as it optimizes for task performance and human effort. Finally, in some settings such as physical interaction with the elderly or the children, subjective sense of comfort, pleasure, and trust could matter the most, making CRA a better choice.

As a result of our studies, we understand that no single interaction scheme can satisfy every aspect of interaction. Hence, the domain and task knowledge should be considered carefully when designing adaptive and proactive robotic partners.

Chapter 6

CONTRIBUTIONS AND FUTURE DIRECTIONS

This dissertation has explored the utility of a role exchange scheme to enable haptic negotiation in human-robot dyads. Our approach consists of identifying distinctive roles in physical human-robot collaboration and defining a system that enables dynamic role allocation using force information. Our contributions can be summarized as follows

1. A novel haptic negotiation model that acts as a shared control framework between a human and a robotic agent is suggested. This haptic negotiation model enables control sharing and role allocation by separating the operations of the human and the robot.

2. An analysis of typical role behaviors for physical human-robot interaction is presented in terms of effort sharing policies between agents.

3. A feedback interaction control architecture that embeds the role behavior into a robotic agent is suggested.

4. A force based role exchange framework is proposed for both virtual and physical domains.

5. The benefits of using the role exchange framework over an equal control scheme is presented through controlled user studies. Specifically, we observed that a role exchange framework has clear benefits over an equal control guidance scheme in terms of task performance, task efficiency, and the energy requirement of the humans.

6. The benefits of enabling multimodal interaction to display the control state to humans is shown. Specifically, we showed that visual and vibrotactile cues built on top of a role exchange framework are helpful in conveying the control state to the users. Also they improve the sense of interaction within the task, as well as making the interface of the system easier to use. Finally, these cues allow humans to trust their robotic partner more.

7. Different ways of implementing dynamic role allocation for physical human-robot interaction is explored through a controlled user study. Our results imply that implementing a smooth role exchanges process is beneficial for improving task performance and decreasing the energy requirements of the human. On the other hand, implementing a distinctive role transition procedure increases the visibility of the role exchange behavior.

Our contributions enable the negotiation process regarding instantaneous intentions existent during physical interaction between a human and a robot. As future work, we would like to investigate operational and task-dependent intentions during interaction. Specifically, we would like to investigate the utility of statistical learning models to recognize conflict moments in physical interaction scenarios. In order to do this, we would like to implement a virtual human-human interaction scenario that resembles joint object manipulation. Focusing on specific conflict moments, we intend to realize automatic segmentation of interaction data, which enables the prediction of conflict situations in interaction.

Another direction we would like to pursue is to explore the role of human characteristics in collaboration. We hypothesize that certain human characteristics, such as aggressiveness, submissiveness, and the levels in between, exist in human-computer collaboration. Discovering such characteristics can be beneficial to alter the extent of guidance provided by the collaborating partner (human or computer) and also to program the computer partner to display more human-like behavior since the results of the questionnaire show that no guidance mechanism we investigated is able to generate this effect.

Additionally, we would like to investigate interaction characteristics in physical collaboration. When working together, humans continuously perform actions to acquire certain low level objectives. For example, when carrying a table as a dyad, partners may rush and choose to finish the task as quickly as possible. In this case, faster task completion is the objective, and pushing the table more strongly is the action that leads to the objective. Alternatively, partners can choose to optimize actions for different objectives such as smooth functioning or minimum effort. Our ability to choose from among a plethora of different objectives is propelled by an evaluation of different possibilities to decide which one is the most important for us. We suggest that we can formulate the dyadic interaction between humans as an optimization problem in which the objectives of the individuals and/or the dyad can be expressed by means of a multiple objective function. We argue that different behavioral patterns, which naturally appear in human-human interaction, can be integrated into a robot simply by adjusting the parameters of this multiple objective function.

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Appendix A

PARAMETERS USED IN THE HUMAN STUDIES

Table A.1: Ball mass and board dimensions

Version	ball mass (kg)	ball radius (m)	board dimensions (m)
Original (Section 3.3)	0.4	4	40×40
Modified (Section 3.4)		1.5	80×80

Table A.2: The stiffness and damping coefficients of the negotiation model used in the original Haptic Board Game explained in Section 3.3 (see Figure 3.1). Note that $K_{p,CT}$ and $K_{d,CT}$ respectively denote the proportional and derivative gains for the PD algorithm. The parameters are optimized to work with a Geomagic® Touch™ (formerly Sensable® Phantom® Omni™) haptic device.

Condition	$K_{p,CT}$ (N/m)	$K_{d,CT}$ (Ns/m)	$K_{p,ON}(N/m)$	$K_{d,ON}(Ns/m)$
NG EC RE	9.0×10^{-7}	9.0×10^{-4}	9.0×10^{-7}	0.00155

Condition	$K_{p,HN}(N/m)$	$K_{p,CN}(N/m)$
NG	0.09	0
EC	0.09	0.09
RE	0.09	$[0.03, 0.09]$

Table A.3: The stiffness and damping coefficients of the negotiation model used in the modified Haptic Board Game explained in Section 3.4 (see Figure 3.1). Note that $K_{p,CT}$ and $K_{d,CT}$ respectively denote the proportional and derivative gains for the PD algorithm. The parameters are optimized to work with a Geomagic® Phantom® Premium™ (formerly Sensable® Phantom® Premium™) haptic device.

Condition	$K_{p,CT}$ (N/m)	$K_{d,CT}$ (Ns/m)	$K_{p,ON}(N/m)$	$K_{d,ON}(Ns/m)$
EC RE VHC	5.0×10^{-6}	3.5×10^{-3}	0.5	0.0015

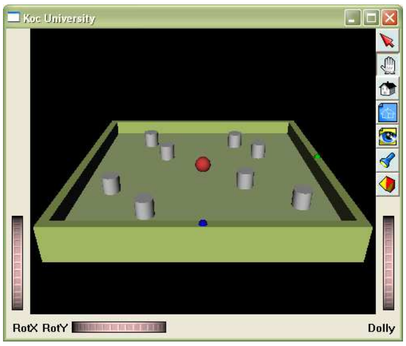
Condition	$K_{p,HN}(N/m)$	$K_{p,CN}(N/m)$
EC	0.25	0.25
RE	$[0.05, 0.45]$	$0.50 - K_{p,HN}$
VHC	$[0.05, 0.45]$	$0.50 - K_{p,HN}$

Appendix B

INSTRUCTIONS USED IN THE HUMAN STUDIES

B.1 Instructions Used by Oguz et al. (2010)

Thank you for volunteering to participate in this study. Please read through this information sheet and ask any questions that you may have before the experiment begins. The experimenter will not answer any questions afterwards.



This experiment requires you to play a simple board game. On the screen, you will see the board with a ball and several cylinders on it. The aim of the game is to hit the cylinders in a specific order in minimum time with maximum accuracy, i.e. your primary goal is to reach the target cylinder.

There will be a haptic device on the right hand side. You shall hold this device with your right hand to manipulate the ball and reach the cylinders. The board can rotate about its mid point; hence it can be tilted. When the board is tilted, the ball will start moving. The board can be tilted only around two axes, hence only moving the stylus in these axes will affect the dynamics of the game. A green and a blue marker moving at the edges of the board will help you visualize the tilt of the board.

Throughout a game, one cylinder will be colored BLUE to indicate that it is the immediate target cylinder you shall touch. If you can hit the target cylinder, its color will turn RED. Untouched cylinders, with the exception of the target, will remain GRAY. The goal is to hit all cylinders, hence to make all cylinders red.

You will play the game 15 times, in 3 sessions. In each session, you will play 5 games in a row and then you will be given a short break. Each game will end once you hit all cylinders, the cylinders will all turn gray and a new initial target will be determined immediately without interrupting the game. You shall see a demonstration in the introductory video which will be displayed after you finish reading these instructions.

During the experiment, the computer MAY interfere with the game to achieve some kind of control. Although computer control is not expected to hinder game play, if it disturbs you please focus on the task and try to complete the game. After the experiment, you will be asked to fill a short questionnaire regarding your experience through the trials.

Before the game starts, you will be given the opportunity to practice, improve your understanding of the game, and get familiar with the haptic device.

The results from this study will be kept for our data analysis. All experimental data will be used anonymously and for research purposes only.

The experiment is expected to take approximately 30 minutes.

Please note

- No identifying information about you will be published in any form.
- You are free to withdraw from the study at any time and without giving reasons for withdrawing.
- Please turn off any electronic devices before the experiment begins.

B.2 Instructions Used by Moertl et al. (2012)

In this experiment, you will be asked to move a table collaboratively with a robotic partner. A handle is attached to the table. Please **pull/push the table using only your dominant hand** (i.e. right hand if you are right-handed) by holding the handle. Please **do not try to lift the table**, all four legs need to be

You will be given 5 "parking configurations“ in a separate sheet. These configurations will also be marked within the experiment area. Your aim is to push/pull the table to these configurations as fast as you can and without colliding into anything (i.e. walls, obstacles). After reaching the fourth parking configuration, you will be asked to return to your initial configuration, which will be your final parking configuration.

The experiment consists of three sessions. In each session you will repeat the same task of reaching all parking configurations and coming back to the initial configuration 5 times. After completing the 5 trials, you will be given a questionnaire, in which you will be asked to comment on the differences in your experience:

Session	**Task**
A	5 x reach 5 parking configurations Questionnaire
B	5 x reach 5 parking configurations Questionnaire
C	5 x reach 5 parking configurations Questionnaire

The robot is capable of finding its way through the environment and is programmed to move the table jointly with a human. At certain times during the task, the robot **may** make decisions depending on its own action plan. The robot will employ different behaviors in sessions A, B, and C. Please pay attention to the differences in robot's behavior:

- A: You and the robot will control the table **equally** at all times to move the table.

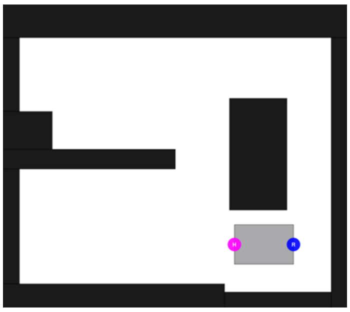
- B: At any point during the task, you may **choose to hand/take over control**. The robot will continuously monitor your actions and release control if you are applying high forces. Also in case of possible collisions, the robot will immediately stop to prevent dangers.

- C: As in B, at any point during the task, you may **choose to hand/take over control**.

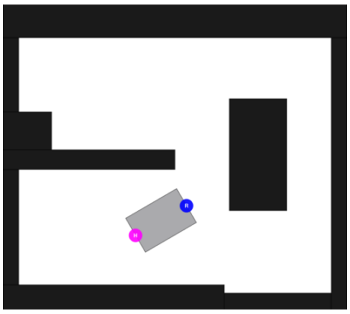
Thank you for volunteering in this study.

Task Description

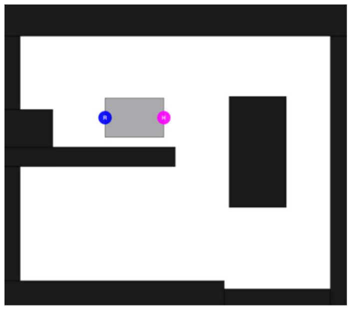
Below is a bird's eye sketch of the experiment area. In the sketches, the table is represented with the light grey rectangle whereas the pink and the blue points respectively denote you and the robot. Your aim during the experiment is to move the table to configurations as shown below. You will hear a ringing sound when you reach these configurations, please move to the next configuration after you hear this sound. The configurations are also drawn on the floor within the experiment area. If you have any questions, please ask them before the experiment begins.



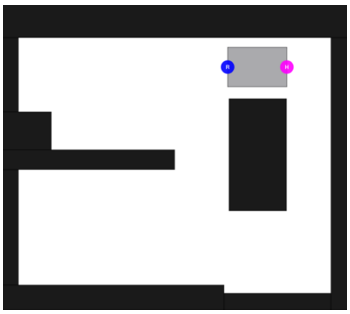
(a) 1^{st} Configuration



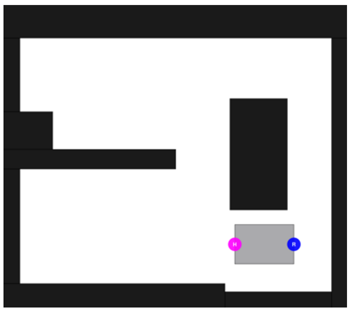
(b) 2^{nd} Configuration



(c) 3^{rd} Configuration



(d) 4^{th} Configuration



(e) 5^{th} Configuration

Appendix C

QUESTIONNAIRES USED IN THE HUMAN STUDIES

C.1 Questionnaire Used by Oguz et al. (2010)

Please take a few minutes to fill out this questionnaire. Please note that this is not a test and there are no right and wrong answers. We thank you in advance for your co-operation.

Please do not discuss this with anyone for one month. This is because the study is continuing, and you may happen to speak to someone who may be taking part.

Note that the questionnaire presented here is used for research purposes only. All data collected from it will be used anonymously and will be kept confidential and no identifying information about you will be published in any form. You are free to withdraw from the study at any time and without giving reasons for withdrawing.

---

1. Sex: (Circle one) M F
2. Age: ________
3. Are you right- or left-handed? (Circle one) Right Left
4. Did you understand the task properly? (Circle one) Yes No
5. Did you experience any problems during the task? (Circle one) Yes No
6. If yes, what were they?

   ____

   ____

   ____

   ____

7. To what extent do you use a computer in your daily life?

   (Mark the right answer)

   (1) (2) (3) (4) (5) (6) (7)

   (1 = Never, 7 = A great deal)

8. Have you ever used this type of force-feedback/touch equipment before?

   (Mark the right answer)

   (1) (2) (3) (4) (5) (6) (7)

   (1 = Never before, 7 = A great deal)

9. Please give your assessment on how well you performed the task.

   (Please mark just one choice)

Poor	( )
Not very good	( )
Neither good or bad	( )
Fairly good	( )
Very good	( )

10. To what extent, if at all, did you have a sense of computer control over the game?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Not at all, 7 = A great deal)

11. To what extent, if at all, did you have a sense of control over the game?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Not at all, 7 = A great deal)

12. To what extent, if at all, did you have a sense of collaborating with the computer?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Not at all, 7 = A great deal)

13. To what extent, if at all, did you have a sense of working against the computer?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Not at all, 7 = A great deal)

14. To what extent, if at all, did you have a sense of working with another human?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Not at all, 7 = A great deal)

15. When you think about your experience, do you remember this as more like just interacting with a computer or working with another person?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Just with a computer, 7 = With another person)

16. If you sensed computer control over the board, to what extent you and the computer were in harmony during the course of the performance of the task?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Not at all, 7 = A great deal)

17. If you sensed computer control over the board, to what extent did the computer hinder you from performing the task?

    (Mark the right answer)

    (1) (2) (3) (4) (5) (6) (7)

    (1 = Not at all, 7 = A great deal)

18. Please write down any further comments that you wish to make about your experience. In particular, what were some of the things that helped you perform the task and what things interfered with the task?

THANK YOU!

Variable	Number of Items	Scale	Items (Question number)
Performance	1	5-pt Likert	9
Humanlikeness	2	7-pt Likert	14, 15
Collaboration	4	7-pt Likert	12, 13, 16, 17
Degree of User Control	1	7-pt Likert	11
Degree of Robot Control	1	7-pt Likert	10

Table C.1: Construction of the scale

C.2 Questionnaire Used by Kucukyilmaz et al. (2011, 2012, 2013)

C.2.1 English Translation

1. Sex M F

2. Age ________

3. Did you experience any problems during the task? Yes No

4. If yes, what were they?

Please indicate the extent to which you agree/disagree with the following statements:

5. I frequently use a computer in my daily life.

Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree

6. I am familiar with haptic devices similar to those used in the experiment.

Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree

Please indicate the extent to which you agree/disagree with the following statements separately for games A, B, and C:

			Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
7.	I was the one who generally controlled the movement of the ball.	A							
		B							
		C							
8.	The computer and I had a common goal.	A							
		B							
		C							
9.	I was a successful player.	A							
		B							
		C							
10.	The interface of the game was easy-to-use.	A							
		B							
		C							

Please indicate the extent to which you agree/disagree with the following statements separately for games A, B, and C:

		Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
11. The game was tiring.	A							
	B							
	C							
12. I liked the interface of the game.	A							
	B							
	C							
13. My performance during the game was poor.	A							
	B							
	C							
14. I felt that I was effective over computer's control on the ball during the game.	A							
	B							
	C							
15. The computer could move the ball correctly when it was controlling the ball.	A							
	B							
	C							
16. I frequently gave the control of the ball to the computer.	A							
	B							
	C							

Please indicate the extent to which you agree/disagree with the following statements separately for games A, B, and C:

		Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
17. It was the computer that generally controlled the movement of the ball.	A							
	B							
	C							
18. The computer collaborated with me while it was directing the ball towards the targets.	A							
	B							
	C							
19. I was successful at changing my control level over the movement of the ball.	A							
	B							
	C							
20. The way I interacted with the game made it enjoyable.	A							
	B							
	C							
21. I had difficulty in understanding the computer's control level on the movement of the ball.	A							
	B							
	C							
22. I was able to give the ball's control completely to the computer whenever I wanted to.	A							
	B							
	C							

Please indicate the extent to which you agree/disagree with the following statements separately for games A, B, and C:

		Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
23. I was able to interact with the computer in different ways during the game.	A							
	B							
	C							
24. Generally I trusted the way that the computer controlled the movement of the ball.	A							
	B							
	C							
25. I would believe it if I was told that I had played the game with a human being instead of a computer.	A							
	B							
	C							
26. Sharing the ball's control with the computer made me feel comfortable.	A							
	B							
	C							
27. The computer's purpose for controlling the ball was the same as that of mine.	A							
	B							
	C							
28. Visual cues that are used in the game made me understand which party held control during the game.	A							
	B							
	C							

Please indicate the extent to which you agree/disagree with the following statements separately for games A, B, and C:

			Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
29.	I was able to understand which party held control during the game by observing the forces I felt through my hand.	A							
		B							
		C							
30.	The computer responded differently in response to my movements.	A							
		B							
		C							
31.	I was able to control the movement of the ball completely whenever I wanted to.	A							
		B							
		C							
32.	The way that the computer played the game made me feel as if I am controlling the ball along with another human.	A							
		B							
		C							

THANK YOU FOR YOUR PARTICIPATION

C.2.2 Original Turkish Version

1. Cinsiyetiniz E K

2. Yaşınız ______

3. Deney süresince hiçbir sorunla karşılaştınız mı? Evet Hayır

4. Eğer cevabınız evet ise bu sorunlar nelerdi?

______

______

______

Lütfen aşağıdaki sorulara ne derecede katıldığınızı belirtiniz:

5. Günlük hayatımda yoğun olarak bilgisayar kullanırım.

Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Ne Katılıyorum Ne Katılmıyorum	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum

6. Deneyde kullanılana benzer dokunsal cihazlara aşinayım.

Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Ne Katılıyorum Ne Katılmıyorum	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum

Lütfen aşağıdaki sorulara ne derecede katıldığınızı oynadığınız üç oyun için ayrı ayrı belirtiniz:

			Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Ne Katılıyorum Ne Katılmıyorum	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum
7.	Topu genelde ben kontrol ettim.	A							
		B							
		C							
8.	Bilgisayar ile ortak bir amacımız vardı.	A							
		B							
		C							
9.	Başarılı bir oyuncuydum.	A							
		B							
		C							
10.	Oyunun arayüzünü kullanmak kolaydı.	A							
		B							
		C							
11.	Oyunu oynamak yorucuydu.	A							
		B							
		C							
12.	Oyunun arayüzü hoşuma gitti.	A							
		B							
		C							

Lütfen aşağıdaki sorulara ne derecede katıldığınızı oynadığınız üç oyun için ayrı ayrı belirtiniz:

		Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Ne Katılıyorum Ne Katılmıyorum	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum
13. Oyundaki performansım kötüydü.	A							
	B							
	C							
14. Oyunda bilgisayarın top üzerindeki kontrolünde etkili olduğumu hissettim.	A							
	B							
	C							
15. Bilgisayar topu kontrol ettiği anlarda topu doğru yönlendirebildi.	A							
	B							
	C							
16. Topun kontrolünü bilgisayara sıklıkla verdim.	A							
	B							
	C							
17. Topu genelde bilgisayar kontrol etti.	A							
	B							
	C							
18. Bilgisayar topu hedeflere yönlendirirken benimle işbirliği yaptı.	A							
	B							
	C							

Lütfen aşağıdaki sorulara ne derecede katıldığınızı oynadığınız üç oyun için ayrı ayrı belirtiniz:

			Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Ne Katılıyorum Ne Katılmıyorum	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum
19.	Top üzerindeki kontrol seviyemi değiştirmekte başarılıydım.	A							
		B							
		C							
20.	Oyunla etkileşim şeklim oyunu eğlenceli kıldı.	A							
		B							
		C							
21.	Bilgisayarın top üzerindeki kontrol seviyesini anlamakta zorlandım.	A							
		B							
		C							
22.	Bilgisayara istediğim zaman topun kontrolünü tamamen verebildim.	A							
		B							
		C							
23.	Oyunda bilgisayar ile farklı şekillerde etkileşim sağlayabildim.	A							
		B							
		C							
24.	Genel olarak bilgisayarın topu kontrol ediş şekline güven duydum.	A							
		B							
		C							

Lütfen aşağıdaki sorulara ne derecede katıldığınızı oynadığınız üç oyun için ayrı ayrı belirtiniz:

			Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Ne Katılıyorum Ne Katılmıyorum	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum
25.	Eğer bu oyunu bilgisayar ile beraber değil de bir insanla oynamış olduğum söylense inanırdım.	A							
		B							
		C							
26.	Topun kontrolünü bilgisayarla paylaşmak kendimi rahat hissettirdi.	A							
		B							
		C							
27.	Bilgisayarın topu kontrol ederken amacı benimkiyle aynıydı.	A							
		B							
		C							
28.	Oyunun arayüzündeki görsel bir takım işaretler topun kontrolünün kimde olduğunu anlamamı sağladı.	A							
		B							
		C							
29.	Oyun sırasında kontrolün kimde olduğunu, elimde hissettiğim kuvvetlerden faydalanarak anlayabildim.	A							
		B							
		C							
30.	Bilgisayar benim hareketlerime cevaben değişik tepkiler gösterdi.	A							
		B							
		C							

Lütfen aşağıdaki sorulara ne derecede katıldığınızı oynadığınız üç oyun için ayrı ayrı belirtiniz:

			Kesinlikle Katılmıyorum	Katılmıyorum	Kısmen Katılmıyorum	Ne Katılıyorum Ne Katılmıyorum	Kısmen Katılıyorum	Katılıyorum	Kesinlikle Katılıyorum
31.	İstediğim zaman topu tamamen ben yönlendirebildim.	A							
		B							
		C							
32.	Bilgisayarın oyunu oynayış şekli bana, topu bir insanla beraber yönlendiriyormuşum gibi hissettirdi.	A							
		B							
		C							

KATILIMINIZ İÇİN TEŞEKKÜR EDERİZ

Variable	Number of Items	Scale	Items (Question number)
Performance	3	7-pt Likert	9, $\underline{13}$, 19
Collaboration	2	7-pt Likert	8, 18, 27
Role exchange frequency	1	7-pt Likert	16
Degree of control	2	7-pt Likert	7, $\underline{17}$
Interaction	5	7-pt Likert	14, 22, 23, 30, 31
Comfort and pleasure	4	7-pt Likert	$\underline{11}$, 12, 20, 26
Haptic cues	1	7-pt Likert	29
Visual cues	1	7-pt Likert	28
Trust	2	7-pt Likert	15, 24
Ease of use	2	7-pt Likert	10, $\underline{21}$
Role exchange visibility	1	7-pt Likert	$\underline{21}$
Humanlikeness	2	7-pt Likert	25,32

Table C.2: Construction of the scale

The scale is constructed using both positive and negative statements. In case a statement bears negative meaning, its contribution to the overall score is calculated as $7 - val$, where val stands for the individual response value. On the other hand, in case a statement is affirmative, its contribution to the overall score is calculated as $val - 1$, where val stands for the individual response value. The negative items are underlined in Table C.2.

C.3 Questionnaire Used by Moertl et al. (2012)

1. Age ________
2. Sex M F
3. Handedness right-handed left-handed

Please indicate the extent to which you agree/disagree with the following statements:

		Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
4. The task required a large amount of mental and perceptual activity (e.g. thinking, deciding, calculating, remembering, looking, searching, etc.)	A							
	B							
	C							
5. The task required a large amount of physical activity (e.g. pulling, pushing, turning, controlling, activating, etc.)	A							
	B							
	C							
6. I needed to be quick to perform the task.	A							
	B							
	C							
7. I was successful in accomplishing the goals of the task set by the experimenter (or myself)	A							
	B							
	C							

Please indicate the extent to which you agree/disagree with the following statements:

			Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
8.	I had to work hard (mentally and physically) to accomplish the task.	A							
		B							
		C							
9.	I felt irritated / stressed / annoyed during the task.	A							
		B							
		C							
10.	During the task, the robot and I acted towards a common goal.	A							
		B							
		C							
11.	My communication with the robot was interactive.	A							
		B							
		C							
12.	I felt that the robot behaved like a human being while moving the table with me.	A							
		B							
		C							
13.	The robot did not have control on the movement of the table, but it was only following my actions.	A							
		B							
		C							

Please indicate the extent to which you agree/disagree with the following statements:

			Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
14.	The way I interacted with the robot made the task enjoyable.	A							
		B							
		C							
15.	I believed that the robot would perform safely and correctly in moving the table.	A							
		B							
		C							
16.	I could easily understand what the robot's plan was during the task.	A							
		B							
		C							
17.	The robot was trying to help me.	A							
		B							
		C							
18.	The robot responded to my actions.	A							
		B							
		C							
19.	I felt comfortable in moving the table with the robot.	A							
		B							
		C							

Please indicate the extent to which you agree/disagree with the following statements:

			Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
20.	I observed and passively obeyed the robot's actions during the task.	A							
		B							
		C							
21.	The robot was good at predicting what I will do.	A							
		B							
		C							
22.	I could trust the robot with moving the table during the task.	A							
		B							
		C							
23.	The actions that the robot performed resembled those a human would do on a similar real-life scenario.	A							
		B							
		C							

Variable	Number of Items	Scale	Items (Question number)
Mental Demand	1	7-pt Likert	4
Physical Demand	1	7-pt Likert	5
Temporal Demand	1	7-pt Likert	6
Performance	1	7-pt Likert	7
Effort	1	7-pt Likert	8
Frustration Level	1	7-pt Likert	9
Collaboration	2	7-pt Likert	10, 17
Interaction	2	7-pt Likert	11, 18
Comfort	1	7-pt Likert	19
Pleasure	1	7-pt Likert	14
Degree of Control	2	7-pt Likert	13, <u>20</u>
Predictability	2	7-pt Likert	16, 21
Trust	2	7-pt Likert	15, 22
Humanlikeness	2	7-pt Likert	12, 23

Table C.3: Construction of the scale

The scale is constructed using both positive and negative statements. In case a statement bears negative meaning, its contribution to the overall score is calculated as $7 - val$, where val stands for the individual response value. On the other hand, in case a statement is affirmative, its contribution to the overall score is calculated as $val - 1$, where val stands for the individual response value. The negative items are underlined in Table C.3.

C.4 NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High