### SORBONNE UNIVERSITÉ

DOCTORAL THESIS

## Kinaesthetic communication : cooperation and negotiation during one dimensional physical interaction with human or virtual partners

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in the

Institute of Intelligent Systems and Robotics



## **Declaration of Authorship**

I, Lucas ROCHE, declare that this thesis titled, "Kinaesthetic communication : cooperation and negotiation during one dimensional physical interaction with human or virtual partners" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Date: 16/10/2018

Signed: Lucas Roche

"It's the questions we can't answer that teach us the most. They teach us how to think. If you give a man an answer, all he gains is a little fact. But give him a question and he'll look for his own answers."

Patrick Rothfuss, The Wise Man's Fear

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## Abstract

# Kinaesthetic communication : cooperation and negotiation during one dimensional physical interaction with human or virtual partners

by Lucas ROCHE

The study of physical Human-Human Interaction (pHHI) has recently become a topic of interest for the robotics community. The objective of this research is to translate findings on how humans behave while interacting together towards improvements in physical Human-Robot Interaction (pHRI). The present thesis follows this process of studying human interaction in order to extract design blocks for human-robot interaction. Focused on the context of lightweight and precise tasks, emphasis is placed on the multidisciplinary nature of human interaction. The resulting work is a blend of robotic design, human-robot interaction, and cognitive psychology.

A first contribution of the thesis is the design and evaluation of a novel experimental setup for the study of lightweight pHHI and pHRI. The setup is composed of two one degree-of-freedom haptic interfaces, combined with a state-of-the-art teleoperation controller allowing precision and transparency while guaranteeing stability and high-frequency force and position data acquisition. Multiple experiments are then presented, which use the previously described setup, each concerning a different aspect of pHHI or pHRI.

The first series of experiments is realized to investigate the effect of haptic feedback on joint decision making in a tracking task. The results confirm the benefits of haptic feedback on performance, and highlight the link between initiative and leadership in conflicting situations during comanipulation. Based on the data collected with human dyads, a Virtual Partner (VP) is designed, able to efficiently perform the task alongside human partners, without hindering the performance of the dyad, nor changing the role dynamic of the subjects. Further experiments are realized to evaluate the VP's performances, and its influence on human behaviour during interaction.

A second series of experiments is organised to explore the interaction between human and virtual partners from a multidisciplinary perspective. The study of kinaesthetic communication is the common focus of the experiments. The results of the first experiment show the influence of teleoperation stiffness on the performance in a comanipulative task. The second one highlights the subconscious differences in interaction with a human or robotic partner. Finally, the third one confirms the efficiency of haptic communication for joint decision making in difficult perception tasks.

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# List of Abbreviations

4C	Four Channels
ADC	Analog to Digital Converter
AGATHE	Assistance au Geste et Applications Thérapeutiques
ANOVA	Analysis of Variance
BBB	BeagleBone Black
CE	Contractile Element
CNS	Central Nervous System
DC	Direct Current
d.o.f	degree(s) of freedom
DOM	Dominance
EEG	Electro <b>e</b> ncephalo <b>g</b> raph
F/T	Force to Torque ratio
fMRI	functional Magnetic Resonance Imagery
HFO	Haptic Feedback from Object
HFOP	Haptic Feedback from Object and Partner
HHI	Human-Human Interaction
HHP	Hidden Human Partner
HRI	Human-Robot Interaction
HVP	Hidden Virtual Partner
IB	Intentional Binding
ISIR	Institut des Systèmes Intelligents et de Robotique
KHP	Known Human Partner
KVP	Known Virtual Partner
MAE	Mean Absolute Error
MAP	Mean Absolute Power
pHHI	physical Human-Human Interaction
pHRI	physical Human-Robot Interaction
PD	Proportional Derivative
PP	Position-Position
ppr	points per rotation
RLS	Recursive Least Square
RMS	Root Mean Squared
SEMAPHORO	Système d'Évaluation de la Manipulation Physique Homme-Robot
ТоМ	Theory of Mind
VP	Virtual Partner

## Chapter 1

# Introduction

The use of robotics in the medical field has been growing steadily for the past decade. In rehabilitation, robots allow the automation of repetitive exercises, relieving the work of practitioners while increasing the availability, intensity and duration of rehabilitation processes for the patients. In surgery, robots are used to reduce the complexity and tediousness of the surgeon's work, while improving the patient safety and recovery. In short, advances in medical robotics are starting to redefine the practice of medicine, to improve people's health and lives around the world.

The AGATHE<sup>1</sup> team at ISIR<sup>2</sup> specializes in robotics for medical applications, ranging from robotized walkers to surgical robots, exoskeletons and prosthesis. The team's vision is centered around the concept of *comanipulation*, defined as the manipulation of an object by two or more agents (humans or robots). For rehabilitation, this means that the robot is used as a tool to guide, help and train patients. For surgery, the goal is to combine the surgeon's expertise with the robot's precision and stability. Overall, most of the applications developed by the team can be categorized as *cobots*.

The concept of cobots was first introduced by Peshkin [Peshkin and Colgate, 2001], who coined the term from collaborative robot. The goal of a cobot is to perform a task alongside a human, towards a common goal. While cobots were originally mostly a thought experiment, significant progress in control, conception and safety in the last decade has allowed their development and deployment in a wide range of applications, from industry to healthcare [Santis et al., 2007, Goodrich and Schultz, 2007, Sawers and Ting, 2014]. The concept of cobot implies cooperation with humans, generally called Human-Robot Interaction (HRI). This interaction, especially in the case of medical robots, leads to physical contact between the human and robot, a situation that is generally referred to as physical Human-Robot Interaction (pHRI).

#### Problematics and research for physical Human-Robot Interaction

PHRI brings many issues to the conception of robots [Hoc, 2000, Santis et al., 2007, Chen et al., 2007, Aracil et al., 2007], which can be classified in three broad categories: The first issue is the **safety** of the human user. In addition, robots need to be able to react to unpredictable human behaviours, and to show a certain degree of **adaptability** to their users or partners. Lastly, in order to reach optimal efficiency, a sufficient level of **communication** must be achieved: the human needs to understand the robot's feedback, and the robot needs to understand the human intentions.

<sup>&</sup>lt;sup>1</sup>Assistance aux Gestes et Applications Thérapeutiques - Assistance to Gesture and Applications for Therapy

<sup>&</sup>lt;sup>2</sup>Institut des Systèmes Intelligents et de Robotique - Institute for Intelligent Systems and Robotics, Paris, France

The safety aspect of pHRI has been widely studied, both in terms of design and control of robots [Lasota et al., 2014], and will not be discussed further in this manuscript.

The design of adaptive and efficient pHRI has been an ongoing subject of research for more than thirty years. Historically, the first approach towards adaptive pHRI was based on impedance control. Impedance control, introduced by Hogan [Hogan, 1985], and extended as variable impedance control, has been used extensively as a mean to provide some flexibility in pHRI. A first study by Ikeura et al. ([Ikeura and Inooka, 1995] and later [Rahman et al., 2000]) used impedance control in combination with human arm impedance analysis. It was also used in [Maeda et al., 2001] and [Corteville et al., 2007] to design robotic assistants for motion, based on minimum-jerk [Flash and Hogan, 1985] motion analysis. [Aydin et al., 2014] used impedance control in combination with Kalman filters to react adaptively to human behaviour. Impedance control however quickly reaches its limits since it often requires a thorough a-priori knowledge of the environment for a smooth execution. Moreover, in most cases these implementations impose a fixed relationship between the human (master) and the robot (slave). The ability to dynamically exchange roles during the task is however a key point for efficient comanipulation [Jarasse et al., 2013, Abbink et al., 2012].

A lot of different solutions have been proposed to introduce dynamic role exchange in pHRI, and most of them observe superior performances with dynamic role allocation rather than fixed role allocation. These solutions can be classified according to the methodology used for role determination. A first approach is to predict human intentions in order to adapt the amount of assistance. This prediction can be made by online estimation of the position or velocity of the human, like in the work of [Aydin et al., 2014], [Maeda et al., 2001] (see Figure 1.1a), or [Thobbi et al., 2011] (see Figure 1.1b). The prediction can also be done using models of the task and human motions, as done in [Evrard et al., 2009, Evrard and Kheddar, 2009]. It can also be done using reinforcement learning algorithms to learn the task [Ikemoto et al., 2009], or human motion primitives [Maeda et al., 2017]. Another approach is to use the interaction forces as a mean to exchange information and negotiate role allocation online: [Mortl et al., 2012] (see Figure 1.1c) used an analysis of redundancy in the dyad to allocate role according to the task. [Oguz et al., 2010, Kucukyilmaz et al., 2011, Kucukyilmaz et al., 2014] used force measures as a way to negotiate the amount of assistance provided in a 2D board game with force feedback. More unique approaches are also considered: [Li et al., 2015] used the minimization of a cost function linked to the task to modulate the robot participation, inspired by game theory. [Stefanov et al., 2009] introduced a theoretical role assignment framework that goes beyond the leader/follower duality, but this framework was not implemented in any real-world experiment.

Most of these current approaches to solve pHRI complications still require to restrain the interaction to a fixed and known environment. Crucially, the solutions to all pHRI problems currently used treat the human as a perturbation that the robot must resolve to succeed its task, and no actual communication occurs between the users and robots.

#### Studying humans to improve robots

One way to develop a more general approach to pHRI would be to take inspiration from the way humans interact together. Humans are indeed able to naturally and efficiently cooperate in comanipulative tasks, with performances that are for now superior to what can be attained in human-robot cooperation. This observation



(A) [Maeda et al., 2001]

(B) [Thobbi et al., 2011]

(C) [Mortl et al., 2012]

FIGURE 1.1: Examples of physical Human-Robot Interaction in the literature.

has led to a recent increase in the study of physical Human-Human Interaction (pHHI) by researchers in robotics. The study of pHHI has already produced an important number of results concerning the behaviour of human-human dyads in comanipulative tasks, and some have successfully been implemented in pHRI.

One of the first and most important results is that humans tend to perform better when operating as a dyad, which has been observed in multiple studies on symmetrical [Reed et al., 2006, Glynn et al., 2001, Ganesh et al., 2014, Santis et al., 2014, Gentry and Feron, 2005, Matsumoto and Inui, 2012, Ueha et al., 2009], and asymmetrical tasks [van Oosterhout et al., 2018]. This increase in performance may however depend on the type of task [Che et al., 2016], and on the presence of force feedback between the humans [Basdogan et al., 2000, Chellali et al., 2011]. Simply reproducing pre-recorded human trajectories however does not yield the same benefits as interacting as a human dyad [Reed and Peshkin, 2008, Avraham et al., 2012, Ganesh et al., 2014]. There seems to be a need for real-time interaction and exchange for the dyadic benefits to take place. This behavior is probably linked to the dynamical role allocation that humans seem to naturally adopt when interacting [Reed and Peshkin, 2008, Feth et al., 2011], which inspired research in PHRI as presented previously. The role exchanges observed in pHHI are both time-varying and dyad-dependent. Furthermore, depending on the task, a significant role imbalance seems to be preferred, as one of the partners stays more dominant than the other [Feth et al., 2011].

Independently from the context, interaction during pHHI is closely linked to the presence of some form of haptic<sup>3</sup> feedback. Haptic feedback indeed seems to have a great influence on the success of dyadic comanipulation between humans. It has been proven to convey emotions [Bailenson et al., 2007] as well as an increased sense of telepresence [Basdogan et al., 2000, Chellali et al., 2011]. It also allows for better learning [Ganesh et al., 2014, Chellali et al., 2011] and performances in tracking tasks, even in cases of conflict [Groten et al., 2013]. In conclusion, many studies point at the haptic channel as an efficient mean of communication between humans [Moll and Sallnas, 2009, Sawers et al., 2017, der Wel et al., 2010, Parker and Croft, 2011, Groten et al., 2013]. This communication is an indirect (implicit) channel, which is sometimes referred to as *feedthrough* [?, ?, ?]

If the existence of this haptic communication ability in human dyads is a wellaccepted theory, the precise mechanisms behind it are yet to be understood. Feth et al. [Feth et al., 2009a] linked haptic communication to the energy exchanges inside the dyad, in order for the partners to negotiate between their individual motion plans.

<sup>&</sup>lt;sup>3</sup>Haptics refers to the perceptual system involving active manual exploration of the environment. It is composed of two afferent subsystems: cutaneous (mostly linked to pressure and vibration receptors in the skin) and kinaesthetic (linked to the perception of motions and to proprioception) [Lederman and Klatzky, 2009].

Takagi et al. [Takagi et al., 2017] propose that the Central Nervous System (CNS) can interpret the force signals from the haptic link and recreate the motion plan of their partner. Simulation with this postulate successfully reproduced the results of a previous study [Ganesh et al., 2014] on the benefits of dyadic interaction for performance and learning improvement. While these studies provide precious insights on the way haptic communication may happen, a lot remains to be understood before we can successfully replicate this ability in robots.

#### How to use robots to study humans

In the field of pHHI research, three main approaches and corresponding experimental setups can be considered to study interaction in human dyads during comanipulation:

- Direct physical contact seems the most obvious solution, allowing various situations to be studied, and natural interaction between the subjects. It is however generally extremely impractical for data acquisition, especially in the case of force data.
- Indirect physical contact through a physical object (comanipulation) allows to solve the problem of force data acquisition by channelling the interaction through an instrumented object. This solution however lacks flexibility in the number of scenarios that can be produced, unless multiple objects are used.
- Indirect contact through teleoperated haptic interfaces, combined with visual feedback or virtual reality, can allow to reproduce a wide variety of situations, and obtain experimental data easily. It is however extremely reliant on the technology used for the interfaces, and is generally more complex to set up.

Studies in the domain of pHHI have been made using both of the later options: [Reed and Peshkin, 2008] (see Figure 1.2a) and [Shahriman et al., 2008] (see Figure 1.2b) used an instrumented physical object to study human-human comanipulation. [Groten et al., 2013] (Figure 1.3a), [Madan et al., 2014] (Figure 1.3b), [Melendez-Calderon, 2011] (Figure 1.3c), or [Ganesh et al., 2014] used coupled haptic interfaces to replicate physical tasks. In most of those studies, the haptic interfaces used have high impedances, and the protocols induce high interaction forces. Although high interaction forces can be desirable, and high impedances are easier to implement while guaranteeing stability, the high apparent impedance of these systems limits the range of tasks that can be studied. In particular, precise and lightweight motions, which can be needed in surgery for example, cannot be studied with these highimpedance interfaces.

#### Human-Human Interaction in other fields of research

While roboticists only recently begun to research pHHI, the interaction between humans has been studied for a longer time in other domains, even if not focused on haptic communication. As early as 1956, Wegner and Zeaman [Wegner and Zeaman, 1956] discussed about the role of social facilitation in performance increase in groups. More recently, the cognitive psychology community has shown interest in the concept of *joint action*, defined as "a social interaction whereby two or more individuals coordinate their actions in space and time to bring about a change in the environment" [Knoblich et al., 2011]. The concept of joint action stems from philosophical theories on the way humans prepare, plan, and perform actions together. Multiple theories on what exactly can be considered a joint action exist ([Gilbert, 1990, Searle, 1990,





(A) [Reed and Peshkin, 2008]

FIGURE 1.2: Examples of setups using comanipulation of an instrumented object for the study of pHHI.



(B) [Madan et al., 2014]

(C) [Melendez-Calderon, 2011]

FIGURE 1.3: Examples of setups using teleoperated haptic interfaces for the study of pHHI.

Bratman, 2014, Pacherie, 2012]). Nuances on cooperation, commitment, awareness or coordination and their requirements for joint action are still debated. Anyway, this interest has led to multiple empirical psychological studies on the subject.

Vesper et al. [Vesper et al., 2011] observed that humans reduce their variability during joint action, in order to facilitate the interpretation of their action. Pezzulo et al. [Pezzulo et al., 2013] showed that humans tend to also change the trajectories of their motion to facilitate interaction, deviating from the biomechanical optimum to add a signal to the action. Multiple studies showed that interpersonal coordination emerges spontaneously between humans, even in the absence of social context [Miles et al., 2009, Delaherche et al., 2012]. Noy et al. [Noy et al., 2011] studied cases of joint improvisation and their results indicate that reciprocal coprediction is essential to coordination. Other studies showed that humans create a mental model of their partner, including a motor representation [Kourtis et al., 2013, Kourtis et al., 2014]. This predictive representation of other people's actions emerges naturally in joint action. In social cooperative tasks, we even create a model for a single entity corresponding to the dyad, a "we-mode" in which the actions of the partner and the self are considered the same [Obhi and Hall, 2011a, Gallotti and Frith, 2013]. Sebanz et al. [Sebanz et al., 2006] moreover showed that in joint action, brain activation is similar for one's partner and one's self, showing once again that we co-represent our partners' objectives and actions.

The use of Electroencephalographs (EEG) or functional Magnetic Resonance Imaging (fMRI) allows to observe the brain mechanisms behind these behaviours in real-time, bridging the gap with neuroscience. One of the most important findings about the neural mechanisms behind joint action was the discovery of mirror neurons [Rizzolatti and Craighero, 2004, Iacoboni et al., 2005], a type of neuron that fires both when we act and when we observe others perform the same act. This led to the discovery of brain regions dedicated to the reproduction and interpretation of others' actions.

This mental representation goes even beyond the representation of others' actions. The Theory of Mind (ToM) framework postulates that we can form representations of others' beliefs and intentions, and recursively of others' beliefs about ourselves (*I think that you think that I think ....*). An interesting study by Devaine et al.[Devaine et al., 2014] showed that humans change their ToM depth (level of recursive belief model) depending on whether a task is presented as social or not.

These social interactions are also studied in social science, where models about competitive and cooperative human interactions have been developed. Game theory [Leyton-Brown and Shoham, 2008] is used in a great variety of domains to explain social behaviors, from economy [Agarwal and Zeephongsekul, 2013] to robotics [Li et al., 2015]. Other relationship models have also been used to describe interactions between humans and the effects of inter-personal pairing [Kenny et al., 2001].

Outside of the specific study of dyadic cooperation, work on haptics [Grunwald, 2008, Lederman and Klatzky, 2009], kinesthesis [Gandevia, 2011], sensory perception and weighting [Ernst and Banks, 2002, Mugge et al., 2009], information and communication theory [Shannon, 1948] can all be integrated to the study of human-human interaction.

In summary, the study of HHI is profoundly multi-disciplinary, and findings from multiple perspectives are available to better our understanding of how humans interact together. Most of these findings can be extrapolated to physical Human-Human Interaction, and thus to comanipulation. Designing and controlling robots based on this knowledge would increase the performance of cobots during pHRI.

#### Positioning of the thesis

The objective of this thesis is to explore the way humans communicate information through haptics, more precisely kinesthesis, and try to translate any findings into design blocks that can be implemented in robots interacting physically with humans.

I decided to focus on lightweight tasks, due to the AGATHE team's research focus, and because the study of such situations is still lacking in the literature. The experiments conducted during the thesis use an experimental set-up based on teleoperated haptic interfaces, because of the flexibility that this solution offers. Experiments from multiple disciplines are conducted, with the objective of combining different approaches to pHHI and pHRI.

A difference is made in the thesis between "low-level" and "high-level" comanipulative tasks. This difference is based on the amount of information exchange required from the participants to achieve the task. Low-level tasks can be performed while relying purely on coordination, for example pointing, target tracking or synchronized motions. High-level tasks require a deeper exchange about a common strategy, and involve intention prediction or detection, common planning, and communication.

The underlying theory behind this work is that it may be possible to build a "kinaesthetic lexicon" of simple processes that can be used for communication through haptics. Enriquez et al. [?] defined these elementary haptic signals as "haptic phonemes", or "the smallest unit of a constructed haptic signal to which meaning can be assigned". They showed that with minimal training, humans can associate a meaning to arbitrary haptic signals composed of a simple waveform of fixed frequency and amplitude. They are also able to later recognize the different signals and remember the associated meaning. Similar work has been conducted by Chan et al. [?], who created "haptic icons" for a similar purpose. Simard and Ammi [?] on the other hand designed "haptic metaphors" to enhance kinaesthetic communication during comanipulation. However, all of the signals used in these studies are artificially designed, and not based on human behavioural observations. We propose that by identifying haptic phonemes used by humans during comanipulation, transferring them to robotic control schemes, and combining them together, we may be able to reconstruct a natural haptic communication between robots and humans.

#### Manuscript structure

The thesis is divided in three parts. The first part presents a preliminary experiment, which exposes the limitations of the setup originally used. It then presents the design and evaluation of an improved setup using teleoperated haptic interfaces, including the mechanical characteristics and control scheme. These new interfaces are then used for the remainder of the thesis experimental work.

The second part presents a series of experiments following the previously explained strategy of studying humans to develop robotic tools for pHRI. A first experiment on pHHI showed that initiative is a crucial factor for conflict resolution in cooperative comanipulative tasks. Based on these findings, a Virtual Partner (VP) is designed, which can perform the task alongside a human. The following two experiments evaluate the VP performances and its influence on human behaviour during task execution.

The last part contains another series of experiments, conducted in collaboration with researchers from domains complementary to my roboticist formation: cognitive psychologists, neuroscientists and philosophers. The objective of these experiments is to explore possibilities beyond the traditional approach to pHRI, and to transpose findings usually related to oral communication towards haptic communication.

## Part I

# Design of an experimental set-up for the study of pHHI and pHRI

### Chapter 2

# **Preliminary Experiments**

#### 2.1 Context

In the context of this thesis, I use haptic interfaces to study physical human-human interaction (pHHI), and later physical human-robot interaction (pHRI). I also choose to focus on studies involving low impedances and low amplitude motions for two main reasons. The first one is a lack of results in the literature for those interactions, while they can be encountered often in our daily lives, and will constitute a challenge for human-robot interaction in the future. The second reason is the interest of the AGATHE team for robotised surgery, where such situations are common place, and where the comprehension of human behaviour in physical interaction is an important step to be mastered.

The first question I decide to investigate is : how well do the results obtained on heavier interfaces translate to situations with lighter interfaces. I choose to reproduce the experiments done by Groten et al. in [Groten et al., 2013]. In their paper, the researchers investigated the influence of haptic feedback in pHHI, and concluded that haptic feedback indeed enhanced the precision and efficiency of human dyads in a tracking comanipulation task. The protocol used in their article uses a one degree-of-freedom (d.o.f) interface, which allows to simplify the dynamics of the task, and to maintain a greater control on the parameters influencing its execution. The tracking task presented is continuous, as opposed to pointing or reaching tasks, which may be insufficient to highlight significant role adaptation in dyads [Takagi et al., 2016]. Finally, the task induces both agreements and conflicts in the dyads motion plans, allowing to explore planning in negotiation situations. The task is thus interactive and both collaborative and competitive, as defined by Jarasse et al. in [?].

This experiment is interesting to us for multiple reasons: the hypothesis studied are interesting, the protocol used is pertinent for the study and easily scalable, and lastly the protocol can be adapted to include pHRI situations for later experiments. I transpose the experimental protocol described in [Groten et al., 2013] to a lightweight setup, to verify if the same results can be observed when the task scale is changed.

#### 2.2 Experimental Protocol

#### 2.2.1 Experimental Setup

The system is constituted of two one d.o.f handles. The mechanical design of each handle, or haptic interface, is inspired from the Stanford University's HapKit [Morimoto et al., 2014] and can be seen in Figure 2.1. The actuation is done by a DC motor connected to the handle through a cable transmission. The user places his/her finger on the handle, and can perform leftward or rightward motions during the task.



FIGURE 2.1: A one degree-of-freedom haptic interface.



FIGURE 2.2: Description of the experimental setup: The two participants each use a one d.o.f haptic interface to share the control over a virtual object. Visual feedback about the position of the object is given on their respective monitors as a cursor.

Encoders are used to acquire the handles positions. The interfaces do not have force sensors, so the interaction forces are deduced from the current driven by the motors.

The controller of the handles and the data acquisition is implemented on a Real-Time operating system (Xenomai - 1 kHz actualization frequency), while the graphical interface runs on another computer. The communication between the two computers uses UDP and TCP protocols through a direct Ethernet connection. The average time-delay in this connection is 0.2 ms and is deemed negligible compared to human response time.

The control of the two handles is composed of two parts: the first part, active all the time, adds a virtual inertia to the handles, simulating a virtual mass. The second part is a Position-Position teleoperation controller, which can be activated to link the handles with a virtual spring in order to keep their position similar during the dyadic experimental conditions.

#### 2.2.2 Experimental task

The experiment consists in a co-manipulative task that two subjects have to complete, either alone or as a dyad. During the experiments, the participants are separated by an opaque curtain in order to prevent any visual clue from their partner. They each wear audio headphones playing white noise during the experiment, to prevent any auditory clue.

#### **Dyadic conditions**

The experimental task is a tracking task: a path (white over black background) is scrolling down on the subjects' monitors, at a speed of 35 mm/s. They use the haptic interfaces described previously to control the position of a virtual object (a single 50g point-mass), represented on their screen as a cursor (see Figure 2.2). The cursor is the same for both subjects, as they share control over a single common virtual object. The subjects are asked to keep the position of the cursor as close as possible to the scrolling path. To further incite each subject to cooperate, they are told that their goal is to maximize the common performance of the dyad. Feedback about the common performance is given by the color of the cursor, which changes based on the distance between the closest path and the cursor (see Figure 2.3):

- Green if  $|X_{cursor} X_{Path}| < 5mm$
- Yellow if  $5mm < |X_{cursor} X_{Path}| < 10mm$
- Red if  $|X_{cursor} X_{Path}| > 10mm$

The path is composed of a procedurally generated succession of curves, divided in two categories (see Fig. 2.4):

- The "BODY" category is composed of sinusoidal-like paths of random directions but fixed duration. The purpose of these parts is to keep the subjects focused on the task between each of the studied parts.
- The "CHOICE" category is the aim of the experiment: at fixed intervals, the path splits into a fork, imposing a clear choice to be made concerning the direction that the subjects need to follow (see Figure 2.3, 2.4). Considering that the subjects can neither see nor hear each other, the only way they can come to



FIGURE 2.3: Illustration of the different decision types: SAME, ONE and OPPO. The data about the choices is recorded from a 2s time window around the path's fork (in red on the leftward figure). Visual feedback about the dyad's performance is given through the color of the cursor (from left to right: green, yellow, red).

an agreement about the direction to choose is to use either the visual feedback from the monitor, or the haptic feedback from the handles.

While the path's structure is strictly the same for both subjects, each subject is encouraged to follow a highlighted trajectory. During the CHOICE parts, subjects receive some information about which side they have to choose [Groten et al., 2013]; this information can differ, creating situations of agreement or conflict, distributed in three cases. This is done by highlighting one of the two paths of the fork (see Figure 2.3):

- **SAME**: Both subjects have the same information, no conflict occurring.
- **OPPO**: Opposite information is given to each subject, inducing a conflicting situation.
- **ONE**: Only one subject has the information. This condition forces the subjects to be ready to take initiative in case they are the only one having information about the path to choose. It is designed to discourage subjects from keeping a passive strategy all along the trials.

The subjects are informed about these choices and the different decision types beforehand.

Each trial lasts 110 seconds, corresponding to a total of 15 decisions distributed equally between SAME, ONE and OPPO decision types. The order of decision types sequence is randomised.

#### **Individual conditions**

In the individual conditions, the overall task is the same, without the negotiation component of the choices. Subjects are still asked to follow the highlighted path when they have one, and to choose a random direction when they don't.

#### 2.2.3 Experimental conditions

Three different experimental conditions are tested in this experiment, to study the influence of haptic feedback on the performances in a comanipulative task:

• **Subjects separated (ALONE)**: Each subject uses his/her own interface and has visual feedback from his/her monitor about his/her position and virtual task.


FIGURE 2.4: Illustration of the experimental task. A pattern composed of sinusoidal-like parts (BODY) and a fork (CHOICE) is repeated 15 times to create each trial. The orientations of the parts are randomly generated.

Each subject can feel his/her own motions and his/her interface's inertia, but nothing from his/her partner. Both subjects perform this condition at the same time independently. This condition is only used for training, and is not the object of any data analysis.

- Haptic-Feedback-from-Object (HFO): In this condition, the two handles are kept free to move independently. Each subject can feel his/her own motions and half of the virtual object's inertia, but nothing from his/her partner. Each subject contributes equally to the task: the position of the cursor is identical on each screen, and computed as the mean of each handle positions:  $x_{cursor} = (x_1 + x_2)/2$ . Hence, the subjects can infer the input of their partner by interpreting the movements of the cursor that are not caused by their own handle's movements.
- Haptic-Feedback-from-Object-and-Partner (HFOP): Bilateral teleoperation control is used to simulate a rigid connection between the interfaces. The positions of the handles are thus kept identical, and visual feedback about this position is given to both subjects. Additionally, the transparency of the setup allows the subjects to feel the efforts applied on the interfaces by both them and their partner. The subjects feel also the full virtual object's inertia (simulated as a 50g mass at the end of the interface).

An illustration of the cursor control for the different experimental conditions can be found in Figure 2.5.

## 2.2.4 Protocol

Each dyad starts the experiment with a block of two trials in ALONE condition in order to familiarise with the interface and its control; this first block is not kept for



FIGURE 2.5: Illustration of the cursor control with the interfaces, in the different experimental conditions. For each case, the top images represent the subjects visual feedback (monitors), and the bottom images the respective positions of their handles.

the following analysis. They continue with the first experimental block, consisting of two trials in either HFOP or HFO condition. The last two trials are done in the other condition (HFO or HFOP).

The order between HFO and HFOP is randomized, and a 40 seconds pause is observed between each trial. At the beginning of the experiment, the subjects are explained the rationale of the setup and told about the different choices in the task. They are also told that two different experimental conditions are tested: they can either cooperate through comanipulation (HFOP), or cooperate with visual feedback only (HFO).

The study involves 34 participants (28 males and 6 females) distributed in 17 dyads. The participants' average age is 23.3. All participants are right-handed and have no previous knowledge of the experiment nor of the experimental set-up. Each dyad provides data for every experimental condition. The first 7 dyads participated in early versions of the experiment, whose data was used to test and tune the protocol, and were later excluded from the analysis. A total of 440 choices are recorded over the course of the experiment (22 choices/trial, 1 trial/condition, 2 conditions/experiment, 10 pairs of subjects).

## 2.3 Results and discussion

#### 2.3.1 Metrics

#### **Root-Mean-Squared Error - RMS**

When studying physical interaction, the first criterion used for evaluation is generally the performance in the realization of the task. In the case of a tracking task, this performance is linked to the precision of the tracking. The tracking error is calculated using RMS error (chosen over simple position error because it amplifies the influence of large errors on the result):

$$RMS = \sqrt{\frac{\sum_{k=1}^{N} (x_{t,k} - x_{o,k})^2}{N}}$$
(2.1)

where  $x_{t,k}$  and  $x_{o,k}$  are respectively the target position and the virtual object position at time step k. Performance is then obtained by comparing the RMS error for a choice to the maximum RMS obtained on the whole sample of trials  $RMS_{max}$ :

$$Performance = 1 - \frac{RMS}{RMS_{max}}$$
(2.2)

This performance indicator is preferred over RMS error for clarity: the better the results, the greater the performance.

#### Mean Absolute Power - MAP

The second aspect of physical interaction that needs to be studied is the physical efforts exerted on and by the interfaces, as well as the interaction force between the participants. The metric used combines both forces and motions to address the physical cost of movements, which leads to energy or power based measures. The MAP criterion introduced in [Groten et al., 2013] is chosen for this measure. It is defined as the sum of absolute values of the power flows from the subjects to their



FIGURE 2.6: Experiment 1 - Results expressed in terms of Power exchange, for the two experimental conditions (HFO and HFOP) and the three decisions types (SAME, ONE and OPPO)

interfaces:

$$MAP = MAP_1 + MAP_2 = \frac{1}{N}\sum_{k=1}^n |P_{1,k}| + \frac{1}{N}\sum_{k=1}^n |P_{2,k}|$$
(2.3)

where  $P_{1,k} = x_{o,k}$ .  $F_{1,k}$  and  $P_{2,k} = x_{o,k}$ .  $F_{2,k}$  are the mean energy flows at the respective haptic interfaces at time step k (with  $x_{o,k}$  the velocity of the virtual object and  $F_{x,k}$  the force applied on interface x).

#### 2.3.2 Results

The results for the MAP parameter are illustrated on Figure 2.6. These results show that the OPPO decision type leads to a greater energy expense for the task than the ONE decision type, itself more demanding than the SAME decision type. These differences are found for both the HFO and HFOP conditions and are statistically significant (p < 0.01 for all), except for the difference between ONE and OPPO on the HFOP conditions (p = 0.25). The force levels are much higher (p < 0.001 for all three conditions) in the HFOP condition compared to the HFO condition, this difference is due to the presence of the interaction force between the two subjects.

Regarding the Performance parameter (Figure 2.7), in both conditions, the SAME performances are significantly better than ONE and OPPO (p < 0.005 and p < 0.001 respectively). The performances for ONE are worse than for OPPO in both conditions, although the difference is only significant in HFO condition. Concerning the differences between HFO and HFOP, significant improvements arise in the HFOP condition compared to the HFO condition, for the ONE and OPPO decision types (p = 0.4 for SAME, p < 0.05 for ONE, p < 0.05 for OPPO).

By studying only the BODY parts were no choices are to be made, it is possible to compare the performances in HFO and HFOP condition for a low-level (tracking only) task. The results show that the performances in HFOP were better than in HFO, with respective performances of 0.702 ( $\sigma_d = 0.12$ ) for HFOP and 0.685 ( $\sigma_d = 0.17$ ) for HFO. This difference is however non significant (p = 0.22).



FIGURE 2.7: Experiment 1 - Results expressed in terms of Performances, for the two experimental conditions (HFO and HFOP) and the three decisions types (SAME, ONE and OPPO)

#### 2.3.3 Discussion

The results obtained in this experiment are generally similar to our expectations and similar to the observations of Groten & Feth [Groten et al., 2013]. These equivalent results, obtained on a vastly different experimental setup, confirm the possibility for humans to quickly communicate intentions via haptic information during cooperative tasks. The experiment was conducted to determine if the results of the reference paper about communication in pHRI - that was almost exclusively obtained for tasks requiring whole arm movements and consequent workload - could be extrapolated to precision tasks.

The MAP parameter results are similar to those found in the reference article [Groten et al., 2013], the only difference being the greater disparity in the force values between the two experimental conditions. This difference can be explained by the very small inertia of our set-up, meaning that even with a simulated mass, the efforts coming from the acceleration of the handles  $F_{handles}$  are comparatively much lower than the efforts coming from the interaction of the two subjects  $F_{inter}$ :

$$F_{handles}$$
 «  $F_{handles} + F_{inter}$   
(HFO) (HFOP)

The MAP results confirm that a non-negligible part of the efforts generated by the subjects during the co-manipulative task is consumed by the interaction forces between the two partners. Moreover, these forces increase significantly with the task difficulty, and more precisely with the need for the partners to negotiate: (a) The interaction force is lower in SAME decision type where no conflict has to be resolved. (b) The interaction force is higher in ONE decision type, where one subject needs to take the lead and guide his/her partner. (c) The interaction force is the highest in OPPO decision type, where a forced conflicting situation has to be solved by the subjects to ensure great performances. The Performance results are also similar to those obtained in [Groten et al., 2013]: the presence of haptic feedback between two partners in a co-manipulative task improves the performances when the subjects need to perform a common choice. A significant improvement is indeed observed in HFOP condition compared to HFO, for both ONE and OPPO decision types, where the partners need to use some form of negotiation to perform.

There are several differences between the results of this experiment and the reference study [Groten et al., 2013], mostly in the relative performance levels for the different decision types. First, in our experiment, the lowest performances correspond to the ONE decision type for both experimental conditions, whereas the OPPO decision type in HFO was expected to be worse. Likewise, the SAME and OPPO decision types led to similar performances in HFOP condition, while we observed that the results in SAME were overall better in all conditions with our setup. Higher overall performances are also observed in our experiment, which could point out an easier task.

## 2.4 Conclusion

The experiment presented in this chapter aimed at transposing an existing protocol in the literature to a lightweight situation (low impedance and motion amplitude), in order to study the effects of changes in scale. The experimental protocol chosen was the one used by Groten et al. in [Groten et al., 2013] both for the hypothesis tested and the practicality of the setup used. The experiment, originally performed on a high impedance interface using whole arm movements was adapted to a setup presenting a low inertia and using finger movements.

The results obtained in the lightweight conditions are in the general direction of those expected from the literature. The presence of haptic feedback enhances the performances of dyads in both experiments, indicating a positive effect on coordination, positioning and joint decision making. Additionally, in both cases the interaction forces deployed by the subject during the task increase in presence of haptic feedback. The interaction forces also increase with the complexity and need for negotiation, indicating that humans can use interaction forces as a way to communicate intentions in pHHI situations. This similarity in results encourages us to think that the scaling on the comanipulative scenario doesn't affect the communication capabilities of the human partners.

Some results however differ from the base experiment, notably in the relative performances obtained for the different types of choices encountered by the subjects. These discrepancies could come from the differences in scale compared to the original protocol. They could however also be explained by the experimental setup used in our experiment. Indeed, the prototype used here has limited capabilities: the actuators only allow for a total force of 1.5N in the handles' extremities. This low force limit constrains us to warn the subjects not to insist too much when in conflict, which could change their behaviour. Moreover, the teleoperation controller used is also limited in stiffness, especially compared to the impedance controller with heavy load used in [Groten et al., 2013]. Finally, the absence of force sensor on the interfaces forces us to approximate the interaction forces acquisition using current consumption by the motors, limiting the precision of the results.

These limitations in the experimental setup prompt us to take the results of this preliminary experiment with caution. We also decide to conceive and build a new

lightweight setup, with improved performances in terms of force limits, control and sensing capabilities.

This will be the subject of Chapter 3.

## **Chapter 3**

# Design and evaluation of lightweight teleoperated haptic interfaces

## 3.1 Context

The work done in this thesis includes multiple studies of physical Human-Human Interaction, mainly centred around comanipulation or haptic transmission of information. The choice was made from the beginning to use teleoperated haptic interfaces for the tasks used in these studies.

The use of teleoperated haptic interfaces brings many advantages when studying physical interaction between humans. Firstly, haptic interfaces focus the interaction on a reduced interaction surface, which makes the parameters of the whole interaction easier to control. Secondly, as robotic systems, the interfaces are equipped with a variety of sensors which accurately record the physical variables of the interaction (positions, forces, contacts ...). These sensors can be easily integrated to the system and do not hinder the natural behaviour of the users. Moreover, the use of haptic interfaces can be combined with visual feedback or virtual reality, allowing the researchers to reproduce a wide variety of situations from the same experimental setup. Lastly, since haptic interfaces by design include force feedback, they can equally be used for studies of pHHI and pHRI.

As a downside, teleoperated interfaces are reliant on the technology used for their design and control, and are generally more complex to set up. This is especially true when the goal is to obtain interfaces with low impedance, which bring additional constraint for actuation, and issues for the control stability.

The simple haptic interfaces initially used in the preliminary experiments (see Chapter 2) showed some strong limitations, both in terms of force transmission and sensing abilities. I thus decided to change and improve the interfaces before further experiments with humans. Multiple commercially available solutions for teleoperated interfaces exist. The most prominent ones for lightweight applications are highlighted in Table 3.1. The main problem with all these interfaces is their cost/performance ratio. Interfaces with a maximal translational force sufficient for our applications are too expensive, and often require the use of proprietary software limiting the amount of possible customisation. For these reasons, there was a need for designing our own interfaces, tailored to the needs of the pHHI and pHRI experiments in lightweight conditions.

These conclusions were also reached by most researcher teams studying pHHI and pHRI. An important proportion of studies in the literature indeed use custommade interfaces. Table 3.2 summarizes these different interfaces. Most of them have

Name	Company	Active dof	Max. Force [N]	Workspace [mm]	Precision [mm]	<b>Price</b> [k€]
Virtuose 3D Desktop	Haption	3	10	520x370x400	0.023	15
Omega 3	Force Dimension	3	12	160x160x110	0.01	20
Falcon	Novint	3	9	100x100x80	0.03	1
Geomagic Touch	Immersion	3	3.3	160x120x70	0.055	1
(formerly Phantomn Omni)	(formerly Sensable)					

TABLE 3.1: Summary of commercially available interfaces for lightweight teleoperation and their specifications.

Laboratory	Articles	d.o.f	Motions by user	Apparent inter- face mass [kg]
Institute of Automatic Control Engineer-	[Groten et al., 2009][Groten, 2011][Groten et al.,	1T	Whole arm movements	10
ing, Technische Universität München, Ger-	2013] [Feth et al., 2009a] [Feth et al., 2009b] [Feth			
many	et al., 2011]			
Dept. of Robotics, Brain and Cognitive	[Santis et al., 2014][Casadio et al., 2006]	2T	Whole-arm movements	3
Sciences, Istituto Italiano di Tecnologia,				
Genova, Italy				
Department of Bioengineering, Imperial	[Melendez-Calderon, 2011][Melendez-Calderon	1R	Wrist rotation	1
College of Science Technology and	et al., 2011][Takagi et al., 2016]			
Medicine, London, UK	[Ganesh et al., 2014][Takagi et al., 2017][Takagi	2T	Whole-arm movements	0.65
	et al., 2018]			

TABLE 3.2: Summary of custom-made interfaces used by researchers in pHHI studies. The apparent masses of the interfaces are calculated as the minimal value during utilization as described in the corresponding articles. For interfaces with rotational d.o.f, the rotational inertia was converted as a single point-mass at the extremity of the end-effector for a more intuitive comparison.

a small number of active d.o.f, in order to reduce the complexity of the design and experimental task and subsequent data analysis. Most of them also use whole-arm movements, or display an important mass and impedance.

Instead, I decide to continue the focus on lightweight and precise comanipulation tasks and thus to design a custom haptic interface with corresponding characteristics. The following chapter presents the target characteristics for the interface, its design, control, and the evaluation of its performances.

## 3.2 Conception and design of the haptic interfaces

## 3.2.1 Requirements

#### Range of motion

For the sake of simplicity, the choice is made to design a one degree of freedom interface. The workspace of the interface will span around 100mm, which is sufficient for a full range of motion of an index finger.

## **Maximal force**

Tanaka et al. [Tanaka et al., 1984] observed that the maximal voluntary abduction force generated by the index finger at the proximal interphalangeal joint (see Figure 3.1) was  $35.81 \pm 6.94N$ . If we consider that the index finger is purely activated by the first dorsal interosseous muscle generating a torque around the metacarpophalangeal joint, then this maximal force at the fingertip can be taken as roughly half of the maximal force at the proximal interphalangeal joint. With some margin, the maximal force generated at the end effector of the interface should thus be greater than 25 N.

#### Maximal inertia/Apparent mass

The lightweight aspect of the interface is a defining component of its design. The aim is to obtain an interface with apparent mass at the end effector lower than 50g gram during manipulation. If we approximate the problem as a point -mass of 50g at the end effector 100mm away from the rotation axis, the corresponding maximal rotational inertia would be  $J_{max} = mr^2 = 5.10^{-4} kg.m^2$ .

#### Friction

The design of the interface should minimize friction. Estimating the maximal values for friction coefficients beforehand is complex since it depends on the geometry and dynamic properties of the final design. For the dry friction coefficient, it is possible to obtain a maximal value based on the maximal force that humans can discriminate when detecting features in tactile exploration (0.4 to 1.1 N according to [Biggs and Srinivasan, 2002]). The dry friction coefficient should not exceed the minimal value, divided by the Force to Torque (F/T) ratio of the interface [Casadio et al., 2006]. In the case of a 100mm arm length, this leads to a maximal dry coefficient of 0.04 Nm.

#### Sensors

Precise acquisition of force and position data is an important part of the work of this thesis, and the interfaces should be equipped with both force and position sensors, with a sufficient resolution (at least 0.1N and 0.05mm respectively).



FIGURE 3.1: Anatomy of the human hand, more specifically of the hand dorsal interossei allowing for abduction and adduction of the fingers.

## **Operation frequency**

The control of the interfaces should allow for the best transmission of forces and positions from one interface to the other. In order to implement performing control scheme, the hardware should be able to reach operation frequencies of at least 1 kHz.

## User safety

The haptic interfaces will be used in experiment with human subjects, and thus must guarantee safety for the users, and compliance to the research ethics guideline.

## **Open source approach**

Very little information is available on most of the custom interfaces developed in the literature. The "hi-5" [Melendez-Calderon et al., 2011] and "Braccio di ferro" [Casadio et al., 2006] are the object of articles of their own and some insight is available on their mechanical design, but even for these, much is left for the reader to guess, especially in terms of control strategies.



FIGURE 3.2: The SEMAPHORO (Système d'Evaluation de la MAnipulation Physique HOmme-RObot - System for the Evaluation of Human-Robot Physical Manipulation) interface. A one degree-of-freedom haptic interface conceived for lightweight and precise bilateral teleoperation.

We decided to go a step further and to publish all of the interface details as open-source materials. One article explaining the design of the interfaces was published in [Roche and Saint-Bauzel, 2018], and all information concerning the mechanical parts, 3D plans, controller and GUI codes can be found on GitHub at: github.com/LudovicSaintBauzel/teleop-controller-bbb-xeno.git. It is under creative commons non-commercial license, meaning that any non-commercial use of this work is authorised.

## 3.2.2 Design of the interface

#### Actuation

To reduce the potential friction and backlash in the system, the interface is designed with a direct drive actuation. The only impedance introduced thus comes from the motor, and the mechanical inertia of the handle. The main drawback of direct drive actuation is the need for more powerful motor to generate a sufficient torque in the absence of reductor. The designed interfaces use two MAXON DC Motors (RE65-250W), connected to a 80mm handle. A representation of the haptic handle is represented in Figure 3.2.

Since the system has only one d.o.f, the Force to Torque ratio can be directly calculated as the inverse of the handle length: F/T = 1/0.08 = 12.5N/Nm.

#### Sensors

A magnetic encoder (CUI INC AMT11) is assembled to the motor shaft. Since the interface is in direct drive, there is no reduction of the motor motion, and it is necessary to use high precision position sensors to ensure the quality of the position control. The encoder precision is 4096 points per rotation (ppr), which can be increased to an actual precision of 4\*4096 ppr if the data is updated on both rising and falling edges of the two encoder channels. This translates to a minimal measurable displacement of the handle of 0.035 mm.

The force applied to the handle is measured with a load cell assembled in the handle's body. The use of a load cell (1 d.o.f sensor) is sufficient in our application since only the torque applied around the motor axis is of interest. This torque is directly proportional to the tangential force applied to the handle, which is measured here with a from-the-shelf load cell. The use of the load cell is further justified by its reduced cost and ease of integration compared to a torque sensor. The load cells can measure forces in the range [-50N; 50N], and have an inherent precision of 0.05N. The data is sampled by a 12 bits ADC, whose precision is greater than the sensor's one.

An additional sensor is used as a safety asset in the interfaces control: small conductive plates are positioned on the tip of the handles, and are connected to an open circuit voltage divider. When a finger comes in contact to the plates, it closes the circuit and a rise in voltage is measured. This is used to adjust the controller in presence or not of human contact.

#### Hardware

The controller is installed on a BeagleBone Black ARM development board (BBB) running a Xenomai Real-Time Operating System. The motors are interfaced with the controller through Maxon ESCON controllers, driven in current control by PWM inputs generated on the BBB. The encoders signals are monitored via the Enhanced Quadrature Encoder Pulse (eQEP) modules of the BBB.

The acquisition cards available with most load cells in the market do not reach acquisition frequencies compatible with real-time control. A custom made acquisition cards (see Appendix A) is thus used to amplify and convert the analog signals from the load cells. This acquisition card uses TI INA125 amplificators and a Maxim MAX1247 12 bits ADC. The finger contact detection is also included in this acquisition card, which sends the data of the four sensors (2 force sensors and 2 finger detectors) to the controller through a SPI bus.

The controller is connected to a second computer used to generate virtual scenarios based on the sensory inputs of the interfaces (position and force). The connection is ensured by TCP network through a direct Ethernet link, introducing a latency of less than 50  $\mu$ s. The data acquisition as well as the control of the motor is running at a 2kHz frequency. Communication with the User Interface is realized at 100 Hz (adjustable according to the needs). Data recording is sampled at 2 kHz.

Figure 3.3 summarises the hardware architecture and data flows between the different parts of the robot.

#### 3.2.3 Control

The principal objective of teleoperation controllers is to reproduce a rigid link between the master manipulator (held by the user) and the slave manipulator (in contact with the environment). The ideal telemanipulator would consist in a stick of zero mass and infinite stiffness, allowing to transfer the distant environment's impedance to the user perfectly. The quality of this impedance transfer is generally called *transparency*, and is the principal criterion when comparing two teleoperators. In pHHI applications, both manipulators have similar roles and are in contact with users. In this configuration, obtaining excellent transparency allows to ensure that both users can accurately feel the displacements and forces applied by their partner.



FIGURE 3.3: Architecture and data flow of the robot hardware.

The second objective of teleoperation controllers is to ensure the stability of the system, to guarantee the safety of the users, environment and robot. Combining stability and transparency in teleoperation is however a tedious problem [Lawrence, 1993, Colgate and Brown, 1994, Weir and Colgate, 2009]. Multiple teleoperation controllers have been proposed since the first telemanipulators were conceived. An comprehensive review of literature on teleoperation can be found in [Hokayem and Spong, 2006].

#### **Position-Position Control**

Historically, the first solution used in teleoperation was to implement Position-Position (PP) control. In PP control, each interface is controlled with a PD controller targeting the position of the other interface. The force command of each interface is therefore expressed as:

$$F_{c,i} = K_P(x_{1-i} - x_i) + K_D(\dot{x_{1-i}} - \dot{x_i})$$
(3.1)

with  $i \in (0, 1)$  designating the interface number,  $F_{c,i}$  the force command for the interface i,  $x_i$  its position, and  $\dot{x}_i$  its velocity.

The result of this controller is a spring-damper-like link between the two interfaces, whose characteristics can be controlled by tuning  $K_P$  (stiffness) and  $K_D$  (damping). The biggest advantage of the PP controller is its simplicity: its implementation only requires position sensors, and its stability can be guaranteed for a range of gain values.

Implementations of PP control however have severe limitations on the maximal stiffness that can be rendered while guaranteeing stability, especially for light manipulators. Better control strategies have since been developed, which are generally preferred in teleoperation applications. PP control however is still used a lot of pHHI research setups for its simplicity [Ganesh et al., 2014, Chellali et al., 2011, Che et al., 2016].

#### Admittance control

Admittance control, introduced by Hogan [Hogan, 1985], can be used to create a stiff link between the interfaces in pHHI setups. In admittance control, the forces applied to the interfaces are used as an input for modelling a virtual object of known impedance. The displacements of the virtual object produced by the applied forces are then reproduced as an output by the interfaces. The resulting control is equivalent to a virtual mass connected to both controllers by a spring/damper link. Admittance control allows to precisely tune the impedance characteristics wanted for the interface. However, to guarantee stability in impedance control, there is a limit on the mass/impedance ratio that can be rendered [Colgate and Brown, 1994]. In the case of lightweight tasks, where the apparent mass of the haptic interface must be kept as low as possible, the range of possible stiffness rendered is generally limited. Moreover, in most dyadic teleoperation scenarios, it is preferable to compensate for the interfaces' impedance, which is not possible in admittance control. Admittance control is used in multiple research setups in the literature, but is not adapted to the applications considered in my thesis, and will thus not be considered further.

#### Control theory for teleoperation

Control theory in teleoperation was refined in the early 90's and allowed to obtain better transparency than PP control.

A teleoperated system can be represented by a hybrid matrix H(s) defined as:

$$\begin{bmatrix} F_1 \\ -V_2 \end{bmatrix} = H(s) \begin{bmatrix} V_1 \\ F_2 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} V_1 \\ F_2 \end{bmatrix}$$
(3.2)

Using the hybrid matrix of the teleoperated system and the definition of the task (environment) impedance  $Z_e = \frac{F_e}{V_e}$  we can express the impedance "felt" by the operator as:

$$Z_t = \frac{F_h}{V_h} = \frac{h_{11}(1 + h_{22}Z_e) - h_{21}h_{12}Z_e}{1 + h_{22}Z_e}$$
(3.3)

Ideal transparency is defined as perfect transmission of environment impedance to the master:  $Z_t = Z_e$ , thus, we can deduct from (3.3) the necessary and sufficient condition for transparency:

#### The Four Channels Architecture

Both Lawrence[Lawrence, 1993] and Yokokohji et al. [Yokokohji and Yoshikawa, 1994] published work on transparency including a theoretical analysis of the teleoperation problem, and realized that perfect transparency can be obtained if both force and position signals are used for the control of both master and slave manipulators. The controller strategy they proposed, called Four Channel (4C) Architecture, is still considered the simplest implementation of a control architecture allowing theoretically perfect transparency in teleoperation. It has been proven to provide the best performances amongst the usual teleoperation schemes [Aliaga et al., 2004].

The standard 4C architecture is presented in Figure 3.4a.



(A) General Four Channel Architecture (B) Implem

(B) Implemented Four Channel Architecture

FIGURE 3.4: Classical version of the Four Channel Architecture (left), and the modified version implemented in the interface (right).

Expressing the transmitted impedance in terms of the block transfer functions leads to:

$$Z_t = \frac{\left[ (Z_m + C_m)(Z_s + C_s) + C_1 C_4 \right] + Z_e(Z_m + C_m + C_1 C_2)}{(Z_s + C_s - C_3 C_4) + Z_e(1 - C_2 C_3)}$$
(3.5)

This architecture allows perfect transmission of impedance from slave to master and from master to slave for the following set of controllers:

$$C_m = K_P + K_D s$$
  $C_s = K_P + K_D s$   
 $C_1 = C_s + Z_s$   $C_2 = 1$   
 $C_3 = 1$   $C_4 = C_m + Z_m$ 

Perfect transparency however requires to include the master and slave impedances in the controllers. These values are only possible to compute accurately with a good measure of the acceleration. Without accelerometers on the system, this value must be obtained by a double derivative of the position measure, which is certain to introduce noise in the system. Zhu & Salcudean [Zhu and Salcudean, 1995] proposed a variation of the perfectly transparent four channels obtained with the following controllers:

$$C_m = K_P + K_D s$$
  $C_s = K_P + K_D s$   
 $C_1 = C_s$   $C_2 = 1$   
 $C_3 = 1$   $C_4 = C_m$ 

Which allows to have perfect transmission of position, while keeping  $Z_t = Z_e + Z_m$ , effectively keeping only the master's impedance felt by the user in addition to the environment impedance. In our application, the master's impedance is low enough (cf Section 3.2.4) for this solution to be acceptable, avoiding the use of accelerometers or double derivative. Moreover, it may be better in certain applications to keep an apparent impedance [Stefanov et al., 2009].

#### Gain adaptation between free and constrained motion

Performance in constrained mode, especially for high environment impedance, is enhanced by increasing the position control gain values: the higher the better. However, higher gain values tend to deteriorate the stability in free mode. In order to compromise with these two contradictory constraints, the control of the interface includes gain scheduling as a way to adaptively react to environment impedance changes. The gains  $K_P$  and  $K_D$  (gains are the same for master and slave controllers) are calculated with the following formula:

$$K_x = K_{x_{min}} + \frac{F_{int}}{F_{int_{MAX}}} K_{x_{MAX}}$$
with  $x = \{P, D\}$  and  $F_{int} = |F_1 - F_2|$ 

$$(3.6)$$

 $K_{x_{min}}$  are chosen as the maximal gains allowing for stability in free mode,  $K_{x_{MAX}}$  are tuned for stability in constrained mode, and to increase the performance while guaranteeing that the system's power limits are not reached during the task.  $F_{int_{MAX}}$  is tuned according to the specific task (in our case, it was estimated that the interaction force between the subjects would not exceed 25N). The gain adaptation can also be used to enhance performances when force data acquisition frequency is low, or when there is a discrepancy between the acquisition frequencies and loop frequencies.

#### Symmetry of the set-up

Most of the literature about teleoperation control addresses the case of a human manipulating the master interface, to interact with a passive environment on the slave side. In our application, both the slave and master sides are in contact with an active human operator. Symmetry of both the interfaces and control are here essential. The four channels architecture can be designed for perfect symmetry of the impedances transmitted on master and slave sides. In the classical 4C controller, the impedance transmitted on master side is  $Z_{env \rightarrow master} = Z_e + Z_m$ , and from the slave's point of view, the transmitted impedance is  $Z_{master \rightarrow env} = Z_s + Z_h$ . In our design, both ends of the teleoperation system are in contact with operators, whose hands impedances can be considered roughly equal ( $Z_h = Z_e$ ) and the master and slave interfaces are identical ( $Z_m = Z_s$ ). In these conditions, the impedances transmitted from one operator to the other are the same in both directions ( $Z_{transmitted} = Z_m + Z_h$ ).

#### Implemented control scheme

The implemented teleoperation scheme is shown in Fig 3.4b. A summary of the gains and their values can be found in Table 3.3.

The main difference with the standard 4C architecture is the symmetry of the interfaces, which are both slaves and masters, and have the same controllers and impedance. Moreover, both interfaces are in contact with an operator rather than an environment, thus the hand impedance  $Z_h$  present on both ends instead of the environment impedance  $Z_e$  on the slave side. Lastly, the gains used in the controllers are here variable (this is not represented on the Figure 3.4b).

#### 3.2.4 System characterisation

The inertia and friction of the interfaces are characterised to ensure they are low enough not to influence the behaviour of the controller and the transmitted impedance.

Variable	Signification	Value
$C_m$	Master Controller	$K_P + K_D s$
$C_s$	Slave Controller	$C_m$
$C_1$	Communication Channel Gain	1
$C_2$	Communication Channel Gain	1
$C_3$	Communication Channel Gain	1
$C_4$	Communication Channel Gain	1
$C_5$	Local force feedback gain	0
$C_6$	Local force feedback gain	0
$K_{P_{min}}$	Minimal value for proportional gain	$3 \times 10^3 N/m^{-1}$
$K_{P_{MAX}}$	Maximal value for proportional gain	$10^5 N.m^{-1}$
$K_{D_{min}}$	Minimal value for derivative gain	$2N.m^{-1}.s^{-1}$
$K_{D_{MAX}}$	Maximal value for derivative gain	$5N.m^{-1}.s^{-1}$
$Z_h$	Operator Hand Impedance	-
$Z_m$	Haptic Interface Impedance	$2.9.10^{-4} kg.m^2$
$T_d$	Communication Channel Delay	< 0.02ms
X1/2	Position of Interface 1/2	-
Fc1/2	Force Command of Motor 1/2	-
F1/2	Force Exerted on Interface 1/2	-
Fh1/2	Force Exerted by Operator 1/2	-

TABLE 3.3: Signification of different control variables and implemented values (if known).

Indeed, the teleoperation control presented earlier reaches optimal performances for low inertia interfaces, and internal friction is not accounted for in the model.

#### **Torque response**

To evaluate the motor open-loop frequency response for torque generation, the haptic interfaces were blocked isometrically, so that the force sensors only measured the efforts coming from the actuation. A sine sweep method was then employed to identify the system parameters. The excitation signal was in the form of:

$$I_{excitation} = A_e \sin(2\pi f_k t) \tag{3.7}$$

With  $f_k$  the frequency of the signal varying from 0.2 Hz to 120 Hz (increments were 0.1 Hz until 2 Hz, and 1 Hz after). The amplitude  $A_e$  of the signal was calculated to generate a 5 N force amplitude on the handle.

$$A_e = \frac{F_e \cdot L_h}{K_m} = \frac{5 \times 0.08}{0.123} = 3.25A \tag{3.8}$$

With  $F_e$  the target force of 5 N,  $L_h$  the distance between the motor axis and the handle fixation, and  $K_m$  the motor torque constant.

Each frequency was tested for 5 periods, on three repetitions. The force response of the signal was recorded and compared to the theoretical force expected according to the excitation. The amplitude of the frequency response is shown in Figure 3.5. The system behaves approximatively as a first order low-pass, with a flat response before 8 Hz, then a fall for the higher frequencies. The bandwidth of the system is 10 Hz, defined with a cut-off at -3 dB. This bandwidth is quite limited to render the full range of human sensorimotor capacities, which partly relies on higher frequencies [Hayward and Maclean, 2007]. It is however sufficient to render the full range of



FIGURE 3.5: Amplitude of the open-loop frequency response of the interface.

human voluntary motions, whose frequencies do not exceed 10 Hz [Hayward and Maclean, 2007].

#### System parameters analysis

The haptic interface without human effort input can be modeled as a simple rigid mass with one degree of freedom in rotation around the motor axis. Considering the motor as sole source of external effort, the dynamic equation of the system can be written as:

$$J_h.\ddot{\theta} = \tau_m - \tau_f \tag{3.9}$$

where  $J_h$  represents the total inertia of the handle,  $\theta$  the angular position of the handle around the motor axis,  $\tau_m$  the motor torque and  $\tau_f$  expressed as:

$$\tau_{f} = \begin{cases} \beta_{1}\dot{\theta} + \beta_{3}sign(\dot{\theta}) & sign(\dot{\theta}) > 0\\ \beta_{2}\dot{\theta} + \beta_{4}sign(\dot{\theta}) & sign(\dot{\theta}) < 0\\ 0 & \dot{\theta} = 0 \end{cases}$$
(3.10)

where  $\beta_1$  and  $\beta_2$  are the viscous friction coefficients and  $\beta_3$  and  $\beta_4$  are the Coulomb friction coefficients [Melendez-Calderon et al., 2011].

This dynamic equation can be expressed linearly as:

$$\tau_m = J_h \ddot{\theta} + \beta_1 \dot{\theta} F(\dot{\theta}) + \beta_2 \dot{\theta} F(-\dot{\theta}) + \beta_3 sign(\dot{\theta}) F(\dot{\theta}) + \beta_4 sign(\dot{\theta}) F(-\dot{\theta})$$
(3.11)

with:

$$F(\dot{\theta}) = \begin{cases} 1 & sign(\dot{\theta}) > 0\\ 0 & else \end{cases}$$
(3.12)

In order to identify the unknown system parameters ( $J_h$ ,  $\beta_{1,2,3,4}$ ), the system is excited in free mode with a pseudo-randomly generated signal during four sessions, each lasting 60 seconds. The signal used has a bounded frequency spectrum, which



FIGURE 3.6: Offline convergence of the system's dynamic parameters estimation using RLS over four excitation sessions of 60 s.

is relatively flat for the 0.1 Hz - 10 Hz range; see [Melendez-Calderon et al., 2011] for the equations of the signal.

Offline Recursive Least Square (RLS) was used in order to estimate the parameters. The convergence of the parameters is shown in Figure 3.6. The average values over the sessions is used as final estimated values for the parameters:  $J_h = 2.96 \times 10^{-4} kg.m^2$ ,  $\beta_1 = 2.40 \times 10^{-4} N.m.s$ ,  $\beta_2 = 2.61 \times 10^{-4} N.m.s$ ,  $\beta_3 = 1.25 \times 10^{-3} N.m$ ,  $\beta_4 = 0.918 \times 10^{-3} N.m$ . The system shows low values of inertia and friction, which are compatible with the teleoperation controller described earlier.

#### **Real-Time performance**

Precision and reliability of the real-time loop of the controller are important characteristics in order to attain optimal performances of the haptic interface. To test the robustness of the implemented controller, various demanding tasks are executed and the loop time execution is recorded. The tasks are akin to those performed during actual usage of the interface (data sampling, motors control, data exchange with the graphical interface...). A total of 5 minutes of recording is analyzed. The target frequency of the loop is 5 kHz. 97.28% of the recorded loops were within 1% error of the target period (i.e between 0.198ms and 0.202ms). 98.27% of the loops were executed between 0.190ms and 0.210ms (less than 5% error), and 99.89% with less than 10% error from the target. An histogram of the loop execution times is represented in Figure 3.7.



FIGURE 3.7: Histogram of the loop time execution of the real-time controller during a five minutes test.

## 3.3 Evaluation of the interface design and performances

#### 3.3.1 Force and position tracking performances with PP and 4C control

Performances of a teleoperation interface can be measured in multiple ways, including: position tracking in free mode (measure of  $h_{12}$ ), force tracking in constrained mode (measure of  $h_{21}$ ), force/velocity relationship in free mode (measured of apparent master impedance). The performances of teleoperated interfaces are generally worse in rigidly constrained mode, i.e when one extremity is immobilized by contact with an infinitely rigid environment.

Figure 3.8a illustrates the trajectories of the interfaces and the forces applied to them when controlled with a Position-Position Controller in constrained motion against a rigid obstacle (with gains  $K_P = 500$ ,  $K_D = 3$ ). The mean force error between  $|F_1|$  and  $|F_2|$  during the test is 0.44 N, corresponding to an average 8.5% relative force error. The average position error is 3.4° (4.8 mm at the end effector).

Figure 3.8b shows the same parameters for interfaces controlled with a 4C Architecture. The mean force error between  $|F_1|$  and  $|F_2|$  during the test is 0.14 N, corresponding to an average of 3.5% of relative force error. The average position error is 0.25° (0.35 mm at the end effector).

Test trajectories in free mode are done by human participants and can be seen in Figure 3.8c and Figure 3.8d. Average position error was 0.27° (0.37 mm) for the PP controller, and 0.045° (0.066 mm) for the 4C controller.

The maximal stiffness rendered by the interface in actual use is measured to reach  $2 \times 10^4 N.m^{-1}$ . The minimal stiffness required to experience the sensation of hardness have been proposed to be around  $10^4 N.m^{-1}$  [Lawrence and Chapel, 1994, Rosenberg and Adelstein, 1993, Hayward and Maclean, 2007]. The performance of the proposed interface should thus be sufficient to simulate a rigid connection between the two handles.

The proposed controller architecture allows for a significant increase in performances compared to a traditional teleoperation controller. It is however unsure how this performance increase translates in real scenarios when the interfaces are used by humans for real tasks. Further experimentations are conducted in this direction.



(C) Free motion - PP

(D) Free motion - 4C

FIGURE 3.8: Example of trajectories in constrained and free motions for the Position-Position (PP) controller and the Four Channels (4C) architecture controller. Forces are represented with the same sign for easier visualization.

#### 3.3.2 Specifications of the final interface

#### Range of motion

The interface workspace with the safety stops at maximal range is an arc of 80*mm*, and 70°, which gives a linear range of 97.6*mm*, in accordance with the 100*mm* target range.

#### Maximal force

Since the system has only one d.o.f, the Force to Torque ratio can be directly calculated as the inverse of the handle length: F/T = 1/0.08 = 12.5N/Nm. The maximal torque that the motor can deploy is limited by the maximal output current of the ESCON controller, which is 15*A*. With a torque/current ratio of 0.123 Nm/A, the maximal force at the handle extremity is  $F_{max} = 15 \times 0.123 \times 12.5 = 23N$ . This is slightly lower than the expected target, but should not hinder the behavior of the interface since the subjects will not need to use their full range of force while interacting.

#### Maximal inertia/Apparent mass

The interfaces have a rotational inertia of  $J_h = 2.96 \times 10^{-4} kg.m^2$ , or a point-mass equivalent of 46*g*, in accordance to the target.

## Friction

The dry friction coefficient are lower than the expected bound  $(1.25 \times 10^{-3} \text{ and } 0.918 \times 10^{-3} \text{ vs } 0.04N.m)$ , and the viscous friction coefficient are sufficiently low to not hinder the operation of the interfaces.

## **Operation frequency**

The interface hardware is able to run smoothly at a 5 kHz frequency, even though a 2 kHz frequency is preferred in practice to synchronize the force sensors and controller frequencies.

## User safety

The interfaces' handle design does not constrain the user's fingers, which limits the risk in case of failure. Moreover, physical safety stops prevent the interface from performing motions wider than acceptable. Lastly, hardware safety is implemented in the form of sensors that detect the contact between the user's fingers and the interfaces, allowing to shift the control strategy if necessary when contact is lost.

## 3.4 Conclusion

This chapter presents the design and evaluation of a novel haptic interface which will be used for the study of Human-Human and Human-Robot physical interaction in lightweight comanipulative tasks. The interfaces have one degree of freedom, are equipped with force and position sensors, and present mechanical characteristics in accordance with our needs: low inertia, low backlash, low friction, adapted to use with one finger, and with sufficient maximal force. The interfaces are controlled with a state-of-the-art teleoperation controller designed for optimized transparency between the two connected interfaces.

Evaluation of both the mechanical and control sides of the interfaces is presented and the interfaces' capabilities are proved adapted to the target use. These haptic interfaces are used for the subsequent experiments in my thesis, with some variations made in the controllers, which are detailed in each chapter.

## Part II

# Design of a Virtual Agent for Human-Robot comanipulation based on human behaviour

## **Chapter 4**

## **PHHI/PHRI** experiments

## 4.1 Context

After the design and validation of our experimental setup, further studies on the kinaesthetic communication in pHHI, and its possible transfer to pHRI are realized. Three experiments are conducted based on the protocol proposed in [Groten et al., 2013] and used in the preliminary experiment (Chapter 2).

The first experiment presented in this chapter is a reproduction of the preliminary test, performed with the new haptic interfaces. This experiment has two main objectives: the first one is to compare the results obtained on the new setup with the results obtained with the previous one. This will allow us to test the generalisability of the results, and the reliability of the protocol and interfaces. The second objective is to record pertinent data on pHHI that can then be used to analyse kinaesthetic communication between humans, and to design a virtual partner able to perform the task alongside a human.

The data from the first experiment is then used to design a Virtual Partner, based on human observation, which is able to perform alongside a human in the experimental task of the first experiment. A second experiment aims at evaluating the performances of the Virtual Partner (VP), while paired with human subjects in Human-Robot dyads. The results in pHRI are compared to the results obtained in pHHI to observe the prospective differences in performances or behaviour induced by the interaction with a robot instead of a human partner. The influence of the partner's nature perception is also studied during the second experiment, by manipulation of the information given to the subjects concerning the identity of their partner (human or virtual).

The third experiment is done in continuity with the second, in order to investigate the influence of the Virtual Partner's behaviour on its partner. Different thresholds governing the VP's approach to negotiation are modulated, while monitoring the role repartition within the Human-Robot dyads in situations requiring a common decision.

Overall, these three experiments are designed to explore the ability of humans to communicate intentions through the haptic channel, and the possibilities to reproduce this behaviour with a Virtual Partner. The long-term objective of this research is to better understand how humans behave in cooperation, to eventually design robots that are meant to perform comanipulative tasks alongside humans.



FIGURE 4.1: Description of the experimental setup: The two participants use a one d.o.f haptic interface to share the control over a virtual object. Visual feedback about the position of the object is given on their respective monitors as a cursor.

## 4.2 Materials and Method

#### 4.2.1 Experimental setup

In the experimental setup, two humans use the haptic interfaces (see Chapter 3) in order to perform various virtual tasks, alone or in cooperation (see Figure 4.1). Both participants are seated at a desk in front of a monitor (19", 1440x900p). The interfaces are placed on their right side, at a height adjusted for comfortable position. The interfaces are manipulated with the index finger of the right hand.

The participants are separated by an opaque curtain in order to prevent any visual clue from their partner. They also wear audio headphones playing pink noise during the experiment, to prevent any auditory clue.

#### 4.2.2 Experimental task

The task used is the same as described in Section 2.2.2.

#### 4.2.3 Metrics

The metrics used for the preliminary experiment are reused here.

#### **Root-Mean-Squared Error - RMS**

The tracking error is calculated using RMS error (chosen over simple position error because it amplifies the influence of large errors on the result):

$$RMS = \sqrt{\frac{\sum_{k=1}^{N} (x_{t,k} - x_{o,k})^2}{N}}$$
(4.1)

where  $x_{t,k}$  and  $x_{o,k}$  are respectively the target position and the virtual object position at time step k. Performance is then obtained by comparing the RMS error for a choice to the maximum RMS obtained on the whole sample of trials  $RMS_{max}$ :

$$Performance = 1 - \frac{RMS}{RMS_{max}}$$
(4.2)

#### Mean Absolute Power - MAP

The Mean Absolute Power is defined as the sum of absolute values of the power flows from the subjects to their interfaces:

$$MAP = MAP_1 + MAP_2 = \frac{1}{N}\sum_{k=1}^n |P_{1,k}| + \frac{1}{N}\sum_{k=1}^n |P_{2,k}|$$
(4.3)

where  $P_{1,k} = x_{o,k}$ .  $F_{1,k}$  and  $P_{2,k} = x_{o,k}$ .  $F_{2,k}$  are the mean energy flows at the respective haptic interfaces at time step k (with  $x_{o,k}$  the velocity of the virtual object and  $F_{x,k}$  the force applied on interface x).

#### **Dominance - DOM**

In OPPO decision types, the dyad has to choose between the two contradictory options that are presented. Since the cursor is common to the two partners, only one of them can "win" i.e reach his/her highlighted side. The partner winning will be defined as the leader for the choice, and his/her partner as the follower. The "Dominance" of a participant is defined as his/her propensity to Lead in the conflicting choices, i.e the percentage of trials in OPPO condition were the subjects impose their choice to their partner.

$$DOM_{s} = \frac{n_{s,win,OPPO}}{n_{OPPO}} \quad (DOM_{s} \in [0,1] and DOM_{1} + DOM_{2} = 1)$$
(4.4)

where  $s = \{1, 2\}$  designates the subject,  $n_{OPPO}$  is the number of trials with OPPO choice, and  $n_{s,win,OPPO}$  is the number of trials where the subject has won the negotiation. Each member of each dyad is classified as a Leader or Follower depending on his/her average overall dominance across the experiment. Levels of dominance are investigated for all experimental conditions.

## 4.3 Experiment 1 : Human-Human Haptic Communication Evaluation

The first experiment is a reproduction of the preliminary test, performed with the new haptic interfaces. The experiment aims at evaluating the reliability of the setup, comparing the results obtained on this setup with the preliminary results, and to acquire data of the human behaviour and motion characteristics during the task.

#### 4.3.1 Experimental conditions

Three experimental conditions are used in the experiment, which aims at highlighting the differences between individuals, dyads that cooperate without force feedback, and dyads which are provided force feedback.

- Subjects separated (ALONE): Each subject uses his/her own interface and has visual feedback from his/her monitor about his/her position and virtual task. Each subject can feel his/her own motions and his/her interface's inertia, but nothing from his/her partner. Both subjects perform this condition at the same time independently.
- Haptic-Feedback-from-Object (HFO): In this condition, the two handles are kept free to move independently. Each subject can feel his/her own motions

and his/her interface's inertia, but nothing from his/her partner. Each subject contributes equally to the task: the position of the cursor is identical on each screen, and computed as the mean of each handle positions:  $x_{cursor} = (x_1 + x_2)/2$ . Hence, subjects can infer the input of their partner by interpreting the movements of the cursor that are not caused by their own handle's movements.

• Haptic-Feedback-from-Object-and-Partner (HFOP): Bilateral teleoperation control (Section 3.2.3) is used to simulate a rigid connection between the interfaces. The positions of the handles are thus kept identical, and visual feedback about this position is given to both subjects. Additionally, the transparency of the setup allows subjects to feel the efforts applied on the interfaces by both them and their partner. The teleoperation control guarantees that the subjects only feel their own interface's inertia, as in the previous conditions.

#### 4.3.2 Protocol

Each dyad starts the experiment with a block of two trials in ALONE condition in order to familiarise with the interface and its control; this first block is not kept for the following analysis. They continue with the first experimental block, consisting of two trials in either HFOP or HFO condition. The ALONE condition is tested afterwards, again with two trials. The last two trials are done in the condition that is not tested in the first block between HFOP and HFO. These two possibilities are presented below:

a) b)	$ALONE(\times 2)$	$\frac{HFO(\times 2)}{HFOP(\times 2)}$	$ALONE(\times 2)$	$\frac{HFOP(\times 2)}{HFO(\times 2)}$
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The order between HFO and HFOP is randomized, and the ALONE condition is always tested between these two, in order to prevent learning effects from one condition to another. A 40 seconds pause is respected between each trial. At the beginning of the experiment, the subjects are explained the rationale of the setup and told about the different choices in the task. They are also told that three different experimental conditions are tested: they can either perform the task alone (ALONE), cooperate through comanipulation (HFOP), or cooperate with visual feedback only (HFO).

The study involved 30 participants (15 males and 15 females) distributed in 15 dyads (6 Male-Male, 6 Female-Female, 3 Mixed). Participants' average age was 21.3 (std 4.3). All participants were right-handed and had no previous knowledge about the experiment or the experimental set-up. All participants were free of any known psychiatric or neurological symptoms, non-corrected visual or auditory deficits and recent use of any substance that could impede concentration. They were all right handed. This research was reviewed and approved by the institutional ethics committee. Each dyad provided data for every experimental condition.

#### 4.3.3 Results

The results of the first experiment are exposed in this section. The independent variables are Experimental Condition (ALONE, HFOP, HFO) and Decision Type (SAME, ONE, OPPO). The changes in efforts (MAP), performances (PERFS) and Dominance (DOM) are studied for each combination of Experimental Condition and Decision Type. Data is analysed over a 2s window around the Choice (see Figure 2.3). Data from all trials are used except for the first block in ALONE condition, for a total of 2 trials (30 choices) for each condition.

When comparing individuals to dyads, statistical analysis of the data can be challenging: subjects cannot be expected to behave the same in solo trials and in dyadic ones, thus a repeated measures design doesn't really fit. On the other hand, an in-between subject design would assume that individuals and dyads are independent entities, which is similarly problematic. In the literature concerning individual-dyads comparison for pHHI tasks, Reed et al. [Reed et al., 2006] and Che et al. [Che et al., 2016] used paired sample t-tests. Feth et al. [Feth et al., 2009a], Van der Wels et al. [der Wel et al., 2010] and Mireles et al. [Mireles et al., 2017] used repeated measures ANOVA. Other articles used ANOVA without precision of the design considered [Matsumoto and Inui, 2012, Ganesh et al., 2014].

The statistical analysis is here performed with repeated measures two-ways ANOVAs, and post-hoc analysis with two-tailed Student's t-tests with Bonferonni correction for multiple comparisons. Results in the next sections are given with the following presentation: ANOVA (*F-value*, *p-value*, *omega-squared size-effect value*), t-tests (*Bonferonni corrected p-value*, *Cohenn's d coefficient for size-effect*). p-values inferior to  $10^{-4}$  are given equal to zero.

#### **Effort measure**

A significant effect on the MAP criterion is observed from both the decision type  $(F(2,416) = 24.18, p = 0, \omega^2 = 0.031)$  and the experimental condition  $(F(2,416) = 366.96, p = 0, \omega^2 = 0.489)$ .

The interaction between decision type and experimental condition also has a significant effect (F(4,416) = 33.94, p = 0,  $\omega^2 = 0.088$ ), post-hoc analysis is thus performed to observe the performance variation in each (decision type)\*(experimental condition) pair.

The MAP values for each Decision Type and Experimental Conditions are presented in Figure 4.2.

The differences in performance are described in tables 4.1 and 4.2.

TABLE 4.1: Influence of the Decision Type over MAP criterion depend
ing on the Experimental Condition
(*): p < 0.05 - (**): p < 0.001

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	$SAME < ONE^*$	$SAME < \mathbf{OPPO}^{**}$	<i>ONE</i> < <b>OPPO</b> **
HFO	$SAME < ONE^{**}$	$SAME < \mathbf{OPPO}^{**}$	$ONE < OPPO^{**}$
ALONE	$SAME \sim ONE$	$SAME \sim OPPO$	$ONE \sim OPPO$

TABLE 4.2: Influence of the Experimental Condition over MAP crite-<br/>rion depending on the Decision Type<br/>(\*): p < 0.05 - (\*\*): p < 0.001

Туре	ALONE vs HFOP	ALONE vs HFO	HFOP vs HFO
SAME	$ALN < \mathbf{HFOP}^{**}$	$ALN < \mathbf{HFO}^{**}$	$HFOP > HFO^{**}$
ONE	$ALN < \mathbf{HFOP}^{**}$	$ALN < \mathbf{HFO}^{**}$	$HFOP > HFO^{**}$
OPPO	$ALN < \mathbf{HFOP}^{**}$	$ALN < \mathbf{HFO}^{**}$	$HFOP > HFO^{**}$



FIGURE 4.2: MAP parameter results for the pHHI experiment. (Error bars represent standard errors of the distributions.)

#### Performances

A significant effect on the performance is observed from both the decision type  $(F(2,416) = 9.54, p < 0.001, \omega^2 = 0.03)$  and the experimental condition  $(F(2,416) = 63.41, p = 0, \omega^2 = 0.20)$ . For the experimental condition, post-hoc analysis reveals that the performances were highest in the ALONE condition, followed by the HFOP condition, with HFO condition leading to the worst performances.

The interaction between decision type and experimental condition also had a significant effect (F(4,416) = 17.38, p = 0,  $\omega^2 = 0.11$ ), post-hoc analysis is thus performed to observe the performance variation in each (decision type)\*(experimental condition) pair. The differences in performance are described in tables 4.3 and 4.4.

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	$SAME \sim ONE$	$SAME > OPPO^*$	$ONE > OPPO^*$
HFO	$SAME > ONE^{**}$	$SAME > OPPO^{**}$	$ONE > OPPO^{**}$
ALONE	$SAME \sim ONE$	$SAME \sim OPPO$	$ONE \sim OPPO$

TABLE 4.3: Influence of the Decision Type over Performance depending on Experimental Condition

TABLE 4.4: Influence of the Experimental Condition over Performance depending on Decision Type

Dec. Type	ALONE vs HFOP	ALONE vs HFO	HFOP vs HFO
SAME	$ALN > HFOP^{**}$	$ALN > HFO^{**}$	$HFOP \sim HFO$
ONE	$ALN > HFOP^{**}$	$ALN > HFO^{**}$	$HFOP > HFO^*$
OPPO	$ALN > HFOP^{**}$	$ALN > HFO^{**}$	$HFOP > HFO^{**}$



FIGURE 4.3: PERFS parameter results for the pHHI experiment. Error bars represent standard errors of the distributions.)

#### Dominance

The Leader won 84.6% of the conflicting choices in the HFOP condition. The difference between Leader and Follower dominance was statistically significant (p = 0, d = 3.67). The Leader won 76.5% of the conflicting choices in the HFO condition. The difference between Leader and Follower dominance was statistically significant (p < 0.001, d = 2.27). The difference of dominance between the HFOP and HFO conditions was not statistically significant for both the Leader and the Follower.

#### 4.3.4 Discussion

This first experiment aims at illustrating differences in performances and interaction forces brought by the addition of tactile feedback in physical Human-Human Interaction (pHHI). 30 participants (15 dyads) use a one degree of freedom dual haptic interface to realize a one-dimensional tracking task.

The results show that the best performances are obtained in the ALONE condition. While this result seems to be in contradiction with the common finding that dyads outperform individuals, it can be explained by the nature of the task. Most of the studies concerning pHHI use tasks which only involve coordination in basic pointing or target tracking, and do not require the subjects to negotiate a choice. The results presented here concern the time period around the decision-making parts of the task, it is thus natural that dyads, who need to come to an agreement about the direction to choose, are outperformed by individuals, who do not have this cognitive burden to handle. Interestingly, this observation holds true even in the SAME condition, in which no conflict between subjects should arise. However, since the subjects cannot know in advance in which decision type they are, we can assume that they still need to consider the possibility of a conflict, thus hindering their performances. In Chapter 5, the same experimental setup is used with a pure tracking task. In these conditions, the performances of the dyads were indeed better than the individuals' ones.

Performances are significantly degraded in the HFOP condition compared to ALONE, with the implementation of a necessity to handle conflicting situations. The performances are even worse in the HFO condition. The superior performances

obtained in HFOP compared to HFO can be explained by the superior quantity of information available to the subject to negotiate the conflicting situation, through the haptic channel.

This hypothesis can be corroborated by the fact that the MAP criterion is significantly higher in HFOP condition than in HFO, meaning that more energy was expended during the task. Since the energy required to accomplish the task is the same for both conditions, this additional energy expenditure is probably used for communication purpose, notably by an augmentation in interaction force. The MAP criterion is the highest in the OPPO trials, followed by the ONE trials and lastly the SAME trials. This result shows a link between the energy consumption and the necessity for negotiation. Indeed, the SAME trials should not lead to conflict, and therefore show the lowest MAP criterion. The ONE trials need some negotiation to take place, since only one participant has information about the target, while the other one needs to extract information about this target, which could be done through the haptic communication channel. The OPPO trials are by definition conflicting and show the highest energy expenditure, in agreement with the proposed hypothesis.

In most trials, the decision making was heavily biased in favour of one of the two participants in most of the experiments. In almost every dyad, one of the two participants acted as a "Leader" and decided the direction in most of the conflicting situations, while the other participant acted like a "Follower". This dominance discrepancy is in agreement with previous results [Feth et al., 2011] and was more pronounced in the HFOP condition than in the HFO condition. This could be explained once again by the higher amount of information available for negotiation, helping the leader cement his role more easily.

Overall, the experimental results obtained in this experiment are similar to those of the preliminary experiment, and the same conclusions can be reached. The new experimental setup is reliable and validated for further use.

## 4.4 Virtual Partner Design

This section presents the design of a virtual agent that will be used in a pHRI scenario. The partner should be able to perform the task alongside a human, without hindering his/her performance, and without taking full control of the task.

To design this virtual partner, data from the Human-Human experiment presented in Section 4.3 is analysed to identify repeatable characteristics of the human behaviour during the task. More precisely, a physical variable is searched that would allow to predict accurately the choice made by the dyad before completion of the motion. This variable would allow to detect the humans' intentions online and react accordingly. In the following paragraphs, such a variable will be called *online predictor*.

#### 4.4.1 Objective

The ideal predictor would allow to predict with 100% accuracy every single choice made by the dyad at the very beginning of each motion in the choice phase. Such a predictor is of course impossible to obtain in practice, and some compromise will have to be made on the acceptable accuracy and duration of the detection phase.

The principal constraints for the choice of the predictor are its accuracy, the time needed for prediction, and the online nature of the detection. The need for accuracy is obvious if the objective is to react correctly to human behaviour. Furthermore, the duration of the prediction must be short enough to leave time for the virtual agent to react. And lastly, the predictor must be fitted for online computation, and thus only rely on information that can be directly observed during the task.

In order to select reasonable target goals for the predictor, some preliminary analysis of the data is performed, in order to assess the average timing of the motions, and choose the analysis time window accordingly. It is considered for the rest of this section that an acceptable predictor should achieve the best accuracy possible, while reaching the prediction more than 0.2 seconds before the end of the motion (based on human visual reaction time [Welford and Brebner, 1980]). The analysis will be performed on a time window of two seconds, centred around the fork in the target path.

#### 4.4.2 Definitions

Each CHOICE Phase (see Section 2.2.2) is composed of a straight line of 1 second duration, followed by a fork where the path splits into two different paths (one on the left and one on the right). The paths merge again after 3 seconds of straight line (see Figure 2.4). The analysis of the data is focused over the decision-making phase of the task, which is estimated to occur over a 2 seconds duration around the fork. Intention detection is performed over a shorter period [ $t_{start}$ ;  $t_{stop}$ ], with  $0 \le t_{start} < t_{stop} \le t_{choice} = 1$  (see Figure 4.4). The horizontal position of the cursor is noted  $X_{cursor}$ . A negative value of  $X_{cursor}$  means that the cursor is on the left, a positive value means that the cursor is on the right. After the fork, the leftward and rightward paths are respectively situated at  $X_{left} = -X_{max}$  and  $X_{right} = X_{max}$ , with  $X_{max} = 80$  pixels  $\simeq 24$  mm.



FIGURE 4.4: Presentation of the CHOICE part and associated variables.

#### 4.4.3 Analysis method

The analysis process is similar for each predictor: A prediction of the outcome of the choice is computed based on the calculated value of the predictor. If the predictor

has a negative value at the end of the analysis, the dyad is expected to choose the leftward path. If on the contrary the value of the predictor is positive, a rightward movement is anticipated. The algorithm then extracts the actual choice made by the dyad based on the final position of the cursor over the CHOICE part. Finally, the algorithm compares the prediction with the actual choice. This process is repeated for each Choice Phase over every sample from pHHI experiments.

#### 4.4.4 Online Predictors

In order for the predictors to be implemented in the virtual agent behaviour, they need to be fitted for online computation. This requires to impose a limit before which the prediction must be completed, so that there is still time to react accordingly to the predicted choice. This limit can either be temporal (the analysis needs to be completed before a time  $t_{stop}$ ), or positional (the analysis is completed before the cursor reaches a certain position). Predictors for both of these categories are tested. Predictors tested here are chosen for their simplicity and possibility to be computed in real-time with the information available from the sensors. Some of them can be found in other studies on pHHI such as [Madan et al., 2014] or [Stefanov et al., 2009].

#### **Temporal limit**

The different online predictors with temporal limit tested are:

- $X_T = X_{cursor}(t_{stop})$ : Position of the cursor at time  $t_{stop}$ .
- $X_M = \sum_{k=1}^{N} \frac{X_{cursor}(k)}{N}$ : Mean position over  $[t_{start}; t_{stop}]$ .
- $V_T = \dot{X}_{cursor}(t_{stop})$ : Instantaneous velocity at time  $t_{stop}$ .
- $V_M = \sum_{k=1}^{N} \frac{\dot{\mathbf{x}}_{cursor}(k)}{N}$ : Mean velocity over  $[t_{start}; t_{stop}]$ .
- $F_M = \sum_{k=1}^{N} \frac{F_{Subject1}(k) + F_{Subject2}(k)}{N}$ : Mean sum of forces applied on the handle over  $[t_{start}; t_{stop}]$ .

#### **Positional limit - The First Crossing Parameter**

The First Crossing (1C) parameter is defined as the side on which the individual position of one of the two subjects exits the interval  $[-X_{thresh}; X_{thresh}]$ . An illustration can be seen on Figure 4.5. Results show that the Leading subjects have statistically lower First Crossings.

The analysis performed to find the First Crossing has two principal parameters: the time at which the analysis starts, and the size of the threshold  $X_{thresh}$ . A later start of the analysis allows to eliminate potential residual perturbations from previous motions of the dyad in the sinusoidal tracking parts. A later beginning of the analysis indeed lead to increased accuracy. Similarly, increasing the threshold size allows to increase the accuracy of the prediction, since a wider motion needs to be made to trigger the First Crossing detection.

If a larger threshold size leads to better performances, it however leads to a later crossing of the threshold, and thus to a longer time before completion of the analysis. Considering the strong time constraint on the analysis duration, it is mandatory to


FIGURE 4.5: Description of the First Crossing parameter: side on which the individual position of a subject first drifts from the central position of 35% of the total target distance. Position difference between subjects is exaggerated for clarity.

select a threshold size which guarantees a short analysis end time, while keeping the best accuracy. Analysis of the data from the pHHI experiment shows that the optimal set of parameters for the task is a threshold size equivalent to 35% of the total target motion, coupled with an analysis beginning at 0.2 second.

## 4.4.5 Accuracy of the predictors

Figure 4.6 (top) exposes the influence of  $t_{stop}$  on the accuracy of the predictors. The curves represented are calculated with a value of  $t_{start}$  which maximizes the accuracy. In order to compare the First Crossing criterion with the others, its accuracy at  $t_{stop}$  is calculated on the set of motions that have already crossed the threshold at  $t_{stop}$ . The proportion of motions detected compared to the total is also indicated on the Figure. The perfect accuracy of the 1C predictor for the earlier values of  $t_{stop}$  thus needs to be taken with caution considering the low number of motions analysed for these parameters.

The accuracy of the 1C predictor is superior to the others for  $t_{stop} < 1.3s$ , and inferior to XM, VM and XT for  $t_{stop} > 1.5s$ . However, at t = 1.5s, more than 90% of the motions are already completed (see Figure 4.6, bottom), meaning that while accurate, the prediction will be obtained too late in most cases. In order to properly predict the outcome, and not just observe it, the value of  $t_{stop}$  should be set so that only a minimal proportion of motions are completed. For example, if a 5% rate of failure is deemed acceptable, the value of  $t_{stop} = 0.75s$  should be chosen, while  $t_{stop} = 0.85s$  is acceptable with a 10% rate of failure. In these conditions, the performances of the 1C criterion are vastly superior to the other predictors (see Table 4.5 for a comparison of accuracies for these times).

The downside of the 1C parameter is that for a fixed  $t_{stop}$ , some of the motions are not detected yet. However, by definition, this parameter doesn't need a fixed  $t_{stop}$ , since all the motions will be detected before they come to completion (see Figure 4.6, bottom). Indeed, the  $X_{thresh}$  of the 1C predictor is always crossed before the motion





Bottom: 1C - Percentage of motions detected when using 1C parameter, as a function of analysis end time. ALL - Percentage of motions completed as a function of time.

Accuracy at 0.75s		Accur	acy at 0.85s	Accuracy at 1.5s		
(5% of motions completed)		(10% of m	otions completed)	(90% of motions completed)		
1C	98.57%	1C	96.17%	XT	98.46%	
VT	72.69%	VT	81.15%	VM	98.07%	
XT	70.77%	FM	74.62%	XM	96.92%	
XM	67.33%	XT	74.42%	1C	<b>95.29%</b>	
FM	65.77%	VM	73.07%	FM	55.77%	
VM	63.46%	XM	70.77%	VT	55.38%	

TABLE 4.5: Accuracy of the predictors at different times during the Choice Phase.



FIGURE 4.7: Schematic functioning of the Virtual Partner algorithm. The algorithm is designed to let the human lead the movement by default. In the absence of human initiative, the virtual partner engages the movement toward its own target.

comes to an end. Moreover, the time between the threshold crossing and the end of the motion is on average 0.22s ( $\sigma = 0.21s$ ).

In conclusion, the First Crossing parameter is both more reliable and more accurate in predicting the choices of the dyads than the other predictors tested. Since the performances reached with this predictor are within the range of the objective, it will be the one used to design the virtual agent. It can be noted that the First Crossing parameter is linked to the notion of initiative in the choice: in more than 95% of the trials, the first subject to initiate a motion towards his goal leads the dyad towards this goal. This observation also holds true in OPPO cases where the subjects have conflicting goals. It seems that humans prefer to let their partner take the lead if they reacted sooner, in order to reduce conflict and enhance the common performance in the task.

## 4.4.6 Virtual Partner Design

The previous findings are used to design an algorithm which can reproduce the observed behaviour, while staying as simple as possible. The objective is to evaluate how this algorithm can perform as a partner in a cooperative precision task.

The algorithm (see Figure 4.7) is designed to model human behaviour. Therefore, the algorithm only has access to information that would be otherwise available to a human subject: (a) The target trajectory; (b) The position of its handle (simulated); (c) The position of the cursor on the monitor; (d) The effort transmitted through the handle. Indirectly, the algorithm can also determine the position of its partner's handle (through the position of the cursor and that of its own handle).

In the BODY parts, the algorithm follows the path. When confronted to a CHOICE, the VP needs to moves to the left/right according to its target. One possibility would be to program a "perfect" step motion that would use the robot speed to maximize the performances. However, doing this would put into question any results we obtain from the pHRI experiments, since any improvement in performances could be attributed to the high performances of the robot. It is thus better to try to reproduce human behaviour, and program the algorithm so that it leads to performances similar to those of a human alone when performing the task without a partner.

Consequently, when confronted to a CHOICE, the algorithm generates a minimumjerk trajectory [Flash and Hogan, 1985] from its current position to the target position, based on the choice it has to make. The First Crossing for this trajectory is generated from a normally distributed variable based on the average and standard deviation of the human behaviour data ( $\mathcal{N}(0.886, 0.160)$ ). In a ONE decision type trials, the virtual partner doesn't have a privileged choice. A direction is thus chosen at random, with a greater First Crossing ( $\mathcal{N}(1.1, 0.1)$ ).

Two situations are then possible: if the human takes initiative<sup>1</sup> before the starting time of the virtual partner, it lets the human lead, entering "Follower Mode". The virtual partner's algorithm then generates a new trajectory to follow. This new trajectory is based on a minimum-jerk model starting at the current position of the virtual partner and ending at the new target. If the human partner did not initiate a motion before the beginning of the virtual partner's trajectory, the virtual partner takes the initiative, entering "Leader Mode", starting its planned motion.

Once the virtual partner has started a motion in "Leader Mode", it is necessary to implement an ability to negotiate in case the human wants to contest the choice. A force threshold  $F_{th} = 0.7N$  is chosen according to the experimental data. The algorithm measures the part of the interaction force between the partners which is directed toward a change of trajectory (negative if the virtual object is currently on the right, positive if the virtual object is on the left). If this interaction force exceeds the force threshold for a duration (time threshold) of  $t_{th} = 0.2s$  (defined from the average human reaction time), the virtual partner switches to "Follower Mode" and generates a new trajectory to follow the human. This change in trajectory can happen multiple times if the conditions are met.

<sup>&</sup>lt;sup>1</sup>Taking initiative is here defined as engaging a movement of the handle resulting in a displacement of superior to 35% of the distance between the starting position and the target.

## 4.5 Experiment 2 : pHRI evaluation of the virtual partner

The second experiment aims at evaluating the performances of the Virtual Partner (VP), while paired with human subjects in Human-Robot dyads.

## 4.5.1 Experimental conditions

- Subjects separated (ALONE): Same as in Section 4.3.
- Haptic-Feedback-from-Object-and-Partner (HFOP): Same as in Section 4.3.
- HVP (Hidden Virtual Partner): The subjects believe they are doing the task together, but are actually performing their task independently, each paired with their own virtual partner (presented in Section 4.4). The subjects have visual feedback concerning their own task and virtual object on their monitor, and can feel the haptic feedback from the virtual partner.
- **KVP (Known Virtual Partner)**: This condition is the same as HVP, with the difference that the subjects are told beforehand that their partner is a virtual agent. This condition is used to compare the behaviour of the human subjects depending on their a-priori about their partner.

## 4.5.2 Protocol

Each experiment starts with a block of two trials in ALONE condition in order to familiarize with the interface and its control, this first block is not kept for the following analysis. The following trials are divided into 3 blocks of two trials (HFOP, HVP, KVP), each separated by one trial in ALONE condition:

ALONE	$HFOP(\times 2)$	ALONE	$HVP(\times 2)$	ALONE	KVP
(×2)	$HVP(\times 2)$	$(\times 1)$	$\overline{HFOP}(\times 2)$	$(\times 1)$	(×2)

The order between HFOP and HVP is randomized, and the ALONE condition is tested between these two, to prevent learning effects from one condition to another. Since the KVP condition relies on informing the participants about the presence of the virtual partner, it is always tested last, to avoid a potential influence on their behaviour during the other conditions.

## 4.5.3 Results

The independent variables are Experimental Condition (ALONE, HFOP, HVP, KVP) and Decision Type (SAME, ONE, OPPO). The changes in efforts (MAP), performances (PERFS) and dominance are studied for each combination of Experimental Condition and Decision Type.

The statistical analysis method and the presentation of the results are the same as in Section 4.3.3.

## **Effort measure**

A significant effect on the MAP is observed from both the decision type ( $F(2, 696) = 30.31, p = 0, \omega^2 = 0.058$ ) and the experimental condition ( $F(2, 696) = 54.43, p = 0, \omega^2 = 0.159$ ).

The interaction between decision type and experimental condition also had a significant effect (F(4, 696) = 14.04, p = 0,  $\omega^2 = 0.084$ ), post-hoc analysis is thus performed to observe the performance variation in each (decision type)\*(experimental condition) pair. The analysis reveals that there is no influence of the Decision Type over the MAP criterion while in ALONE condition, and that the differences between HFOP, HVP and KVP conditions are mainly significant in the OPPO decision type. The differences in performance are described in Tables 4.6 and 4.7.

TABLE 4.6: Influence of the Decision Type over MAP (\*) : p < 0.05 - (\*\*) : p < 0.001

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	$SAME < ONE^*$	$SAME < \mathbf{OPPO}^{**}$	<i>ONE</i> < <b>OPPO</b> **
HVP	$SAME < ONE^{**}$	$SAME < \mathbf{OPPO}^{**}$	$ONE < \mathbf{OPPO}^{**}$
KVP	$SAME < ONE^{**}$	$SAME < \mathbf{OPPO}^{**}$	$ONE < \mathbf{OPPO}^{**}$
ALONE	SAME = ONE	SAME = OPPO	ONE = OPPO

TABLE 4.7: Influence of the Experimental Condition over MAP (\*) : p < 0.05 - (\*\*) : p < 0.001

Dec. Type	ALONE vs HFOP	ALONE vs HVP	ALONE vs KVP
SAME	$ALN < \mathbf{HFOP}^{**}$	$ALN < \mathbf{HVP}^{**}$	$ALN < \mathbf{KVP}^{**}$
ONE	$ALN < \mathbf{HFOP}^{**}$	$ALN < \mathbf{HVP}^{**}$	$ALN < \mathbf{KVP}^{**}$
OPPO	$ALN < \mathbf{HFOP}^{**}$	$ALN < \mathbf{HVP}^{**}$	$ALN < \mathbf{KVP}^{**}$
Dec. Type	HFOP vs HVP	HFOP vs KVP	HVP vs KVP
SAME	$HFOP > HVP^{**}$	$HFOP > KVP^*$	$HVP < \mathbf{KVP}^{**}$
ONE	$\mathbf{HFOP} > HVP^{**}$	$HFOP > KVP^*$	$HVP \sim KVP$
OPPO	$HFOP > HVP^{**}$	$\mathbf{HFOP} > KVP^{**}$	$HVP < \mathbf{KVP}^*$

## Performances

A significant effect on the performance is observed from both the decision type  $(F(2, 696) = 45.25, p = 0, \omega^2 = 0.086)$  and the experimental condition  $(F(3, 696) = 69.22, p = 0, \omega^2 = 0.199)$ . The interaction between decision type and experimental condition also had a significant effect  $(F(6, 696) = 17.55, p = 0, \omega^2 = 0.023)$ , post-hoc analysis is thus performed to observe the performance variation in each (decision type)\*(experimental condition) pair. The differences in performance are described in Tables 4.8 and 4.9.

## Dominance

The Leader won 84.6% of the conflicting choices in the HFOP condition. The difference between Leader and Follower dominance was statistically significant (p = 0, d = 3.67). The Leader won 59.3% of the conflicting choices when unknowingly paired with the virtual partner (HVP condition). The difference between Leader and Robot dominance was not statistically significant (p = 0.51, d = 0.76). The Leader won 66% of the conflicting choices when knowingly paired with the virtual partner (KVP



FIGURE 4.8: MAP parameter results for the pHRI experiment. Error bars represent standard errors of the distributions.)



FIGURE 4.9: PERFS parameter results for the pHRI experiment. Error bars represent standard errors of the distributions.)

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	$SAME \sim ONE$	SAME $> OPPO^*$	$ONE > OPPO^*$
HVP	$SAME > ONE^{**}$	$SAME > OPPO^{**}$	$ONE > OPPO^{**}$
KVP	$SAME > ONE^{**}$	$SAME > OPPO^{**}$	$ONE > OPPO^{**}$
ALONE	$SAME \sim ONE$	$SAME \sim OPPO$	$ONE \sim OPPO$

TABLE 4.8: Influence of the Decision Type over Performance depending on Experimental Condition

TABLE 4.9: Influence of the Experimental Condition over Performance depending on Decision Type

Dec. Type	ALONE vs HFOP	ALONE vs HVP	ALONE vs KVP
SAME	$ALN > HFOP^{**}$	$ALN \sim HVP$	$ALN > KVP^{**}$
ONE	$ALN > HFOP^{**}$	$ALN > HVP^{**}$	$ALN > KVP^{**}$
OPPO	$ALN > HFOP^{**}$	$ALN > HVP^{**}$	$ALN > KVP^{**}$
Dec. Type	HFOP vs HVP	HFOP vs KVP	HVP vs KVP
SAME	$HFOP < HVP^{**}$	$HFOP < \mathbf{KVP}^{**}$	$HVP \sim KVP$
ONE	$HFOP \sim HVP$	$HFOP \sim KVP$	$HVP \sim KVP$
OPPO	$HFOP \sim HVP$	$HFOP \sim KVP$	$HVP \sim KVP$

condition). The difference between Leader and Robot dominance was not statistically significant (p = 0.09, d = 1.24). The Follower won 29.3% of the conflicting choices when unknowingly paired with the virtual partner (HVP condition). The difference between Follower and Robot dominance was statistically significant (p < 0.001, d = -1.81). The Follower won 31.9% of the conflicting choices when knowingly paired with the virtual partner (KVP condition). The difference between Follower and Robot dominance was statistically significant (p < 0.001, d = -1.81).

The Leader was statistically more dominant in the HFOP condition than in the HVP condition (p < 0.001, d = 1.16). The differences between HFOP and KVP, or between HVP and KVP were not significant.

The Follower was statistically more dominant in the KVP condition than in the HFOP condition (p < 0.05, d = -0.85). The differences between HFOP and HVP, or between HVP and KVP were not significant.

## **Robot Alone**

When the virtual partner executes the task alone (ROBOT), it reaches performances similar to humans alone, but better than every other condition. (ROBOT vs ALONE, p = 0.42; ROBOT vs other experimental conditions, p<0.001).

Average performances across decision type:

Condition	Mean Perf	σ
Alone	0.746	0.067
ROBOT	0.735	0.110
HVP	0.688	0.145
KVP	0.676	0.157
HFOP	0.633	0.141

## 4.5.4 Discussion

In the second experiment, the virtual partner designed in Section 4.4 is evaluated in cooperation with human participants on the same tracking task previously introduced.

The KVP and HVP conditions lead to similar Performances (no significant statistical difference found between the two conditions), meaning that the a priori knowledge of the nature of the partner doesn't influence the performances on the task. In some dyads, this a priori knowledge can have some influence on the dominance: some participants tend to lead more in conflicting situation in KVP than in HVP (these results are not statistically significant for all dyads). It seems that some humans tend to be more assertive when they know they operate with an artificial agent rather than a human. This hypothesis could be corroborated by the fact that the MAP criterion is greater in KVP than in HVP, showing a greater amount of communication/contestation when participants are aware that they are paired with the virtual partner.

The virtual partner allows to reach performances at least as good as human partners, even in conflicting situations. Indeed, the performances in the HVP and KVP conditions are always equal or superior to the performances in HFOP condition. Furthermore, this result does not come from higher performances of the robot guiding or leading the human, since the robot alone is tuned to reach performances similar to humans alone, and the distribution of decision leading (Dominance) is even between the human and the virtual partner. This increase in performances for the human-robot dyads coincides with a decrease in energy expenditure from the human, but only in the HVP condition, where the humans do not know they are cooperating with a virtual agent.



FIGURE 4.10: Dominance results of the pHHI/pHRI experiment: a significant dominance discrepancy is found between Leader and Follower in pHHI condition. Additionally, Leaders in HFOP condition tend to stay Leaders in pHRI condition. Similarly, Followers in pHHI conditions stay followers when paired with the Virtual Partner.

## 4.6 Experiment 3 : modulating the virtual partner dominance

## 4.6.1 Context

A limitation of the second experiment is that the force and time thresholds used for the negotiation phase with the virtual partner are fixed. While this doesn't seem to disturb the participants, some additional flexibility could be added in the negotiation. Those fixed thresholds however led to an interesting result: human participants that tend to be Leader in HFOP condition stay overall Leaders in the HVP condition (although in a less pronounced way). Likewise, Followers in HFOP behave the same when unknowingly paired with the robot (once again in a less pronounced way). These results can be seen in Figure 4.10.

We hypothesize that the Leader/Follower behaviour of humans can be modeled by an intrinsic time/force threshold for negotiation, which varies for each person. The behaviour in HVP could be explained by the fact that our tuning of the thresholds happens to be slightly lower than those of a human with Leader personality, but higher than those with a Follower personality. Similarly, the more dominant behaviour of humans in KVP condition could be explained by humans having higher thresholds if they know their partner is artificial, and/or if they are more confident in the task. If this hypothesis is true, it should be possible to influence the behaviour of partners in human/robot dyads by controlling the time/force thresholds available for negotiation. An experiment in pHRI settings is conducted to test the hypothesis and investigate the influence of the Virtual Partner's thresholds on its dominance, and the behaviour of its human partners.

The experiments and parts of the data analysis of this section were realized by Anish Monachan, intern at ISIR, under my supervision.

## 4.6.2 Negotiation thresholds

## Force and time thresholds

The virtual partner used in the experiments includes a possibility for negotiation in cases of conflict with the human (see Section 4.4 for details). When the robot is leading the trajectory and the human disagrees on the chosen direction, he/she can contest

this choice by applying a force in the opposite direction. If the applied interaction force is superior to a fixed force threshold  $F_{th}$  during a fixed duration (time threshold)  $t_{th}$ , the virtual partner yields and concedes the lead to the human.

In the original tests, the values of  $F_{th}$  and  $t_{th}$  were chosen as the mean interaction forces and duration observed in the data from the first (pHHI) experiment, in the OPPO trials in HFOP condition. These values were not used as variables in the task, because it would have added too much complexity to the experimental protocols. These thresholds however influence the behaviour of the virtual partner, and thus it is reasonable to think that they can influence the behaviour of the human subjects, and the role dynamic within the dyad. This potential influence is investigated in this third experiment.

#### Muscle energy expenditure threshold

In the experimental task used, the subjects must negotiate which direction they will follow together. This negotiation occurs just before the path's forking, in a straight line segment. Experimental observations suggest that the dyad remains mostly immobile during this phase, but that interaction forces appear between the two subjects. These interaction forces are greater in more conflicting scenarios (OPPO compared to ONE or SAME). These interaction forces could be seen as the negotiation, with subjects forcing against each other, until one of them yields. If this is the case, a threshold based on muscle energy expenditure during the negotiation would make sense, as subjects would have to choose the amount of energy they are willing to spend in order to win the negotiation.

The power consumed by muscles during activity depends on multiple factors, including amount of activation, lengthening/shortening velocity, fibre muscle types, and actual mechanical work produced. Models predicting the energy expenditure of mammals' muscles have been the subject of numerous biomechanics studies for close to a century. The first model describing muscle activity was established by Hill in 1938 [Hill, 1938]:

$$(v+b)(F+a) = b(F_0+a)$$
(4.5)

where *F* is the load in the muscle,  $F_0$  is the maximum isometric tension generated by the muscle, *v* is the velocity of contraction, *a* is the coefficient of shortening heat (dependent on the muscle), and  $b = av_0/F_0$ , with  $v_0$  the maximal velocity (when *F*=0).

This model describes the link between the muscle contraction velocity and the load produced during contraction. While subject to a fair bit of criticism within the community, the Hill model has inspired most of the current biomechanical models for muscle simulation.

One of the most advanced models for human muscle energy expenditure can be found in the work of Umberger et al. [Umberger et al., 2003], based on previous work by Nagano et al. [Nagano and G.M. Gerritsen, 2001]. This model combines most of the previous ones from the literature, with corrections made to adjust the model to fit experimental data.

According to the model, the power consumption  $\dot{E}$  (in Watt per kilogram of muscle -  $W.kg^{-1}$ ) of human muscles can be derived as the sum of three independent sources:

$$\dot{E} = \dot{h}_{AM} + \dot{h}_{SL} + \dot{w}_{CE} \tag{4.6}$$

 $\dot{w_{CE}}$  represents the amount of mechanical work produced by the Contractile Element (CE) of the muscle. It can be derived from conventional mechanics as :

$$\dot{w_{CE}} = -\frac{F_{CE}V_{CE}}{m},\tag{4.7}$$

with  $F_{CE}$  the load produced by the muscle considered,  $V_{CE}$  the velocity of the extremity, and *m* its mass.

 $h_{SL}$  represents the shortening and lengthening heat rate, i.e. the amount of energy dissipated as heat during the change of length of the muscle. This value is often estimated as a proportional to the contraction velocity:  $\dot{h}_{SL} = \alpha_S . V_{CE}$ . The shortening heat coefficient  $\alpha_S$  varies with the type of muscle fiber studied, and thus its value for the whole muscle depends on the ratio between Fast-Twitch (FT) fibers and Slow-Twitch (ST) fibers in its composition. In the model proposed in [Umberger et al., 2003],  $\alpha_S$  is calculated as:

$$\alpha_{S(ST)} = \frac{4 \times 25}{\tilde{V}_{CE(MAX-ST)}} \text{ and } \alpha_{S(FT)} = \frac{1 \times 153}{\tilde{V}_{CE(MAX-FT)}}$$
(4.8)

 $h_{AM}$  represents the activation and maintenance rate of the muscle. This term is only dependent on muscle composition and level of activation. At maximal activation,

$$h_{AM} = 1.28 \times \% FT + 25 \tag{4.9}$$

with %*FT* representing the percentage of Fast-Twitch fibers in the composition of the considered muscle. For lower levels of muscle activation,  $h_{AM}$  is generally considered to be linearly scaling, although Umberger et al. argue that this slightly underestimates the actual activation heat rate for the lowest activation levels. They propose a correction coefficient which varies with the ratio between the level of stimulation from the neural command of the muscle and its actual level of activation. While interesting, this adjustment goes beyond the scope of what is needed for our description, and we will simply consider that for a given muscle,  $h_{AM}$  only varies with the level of activation.

The relationship between muscle activation and load is reported to be linear for multiple muscle and muscle groups [Miller, 2014], including the dorsal interosseous muscles of the hand [S. et al., 1973], which are used to move the index finger left and right, as when using the haptic interface in the experiment. We can thus consider that the heat activation rate is proportional to the load produced by the muscle.

If we make the assumption that the negotiation is based on the interaction force, and that it happens while no motions are realized, then  $\dot{h_{SL}}$  and  $\dot{w_{CE}}$  are both equal to zero during this phase since  $V_{CE} = 0$ . In this (simplified) situation, the energy expenditure of the muscles only comes from the heat activation rate, which is proportional to the muscle load produced.

$$\dot{E} = h_{AM} = \alpha_{AM} F_{CE} \tag{4.10}$$

with  $\alpha_{AM}$  a constant that could be derived experimentally.

Over the negotiation phase, the total energy expended is thus:

$$E_{negotiation} = \int_{t0}^{tf} \dot{E}dt = \int_{t0}^{tf} \alpha_{AM} F_{CE}dt$$
(4.11)

If we assume that the force threshold and time threshold for one subject are constant during the negotiation phase, then we can derive an energy threshold corresponding to the acceptable amount of muscle energy expenditure used for negotiation:

$$E_{th} = \int_{t0}^{t_{th}} \alpha_{AM} F_{th} dt = \alpha_{AM} F_{th} t_{th}$$
(4.12)

This energy threshold allows to combine the force and time threshold in a more convenient way, and if the experimental data backs up the relationship between dominance and energy threshold, it would be a good metric to study human-robot haptic negotiation.

## 4.6.3 Materials and Method

## Experimental setup and task

The setup used for this experiment is identical to the previous ones (see Section 4.2.1). The task is similar to the previous one. The only difference is the repartition of choices: since this study is based on the Dominance criterion, which is only relevant in OPPO trials, the proportion of the latter is increased in comparison to the others. Some SAME and ONE trials are kept to prevent the subjects from keeping the same strategy throughout the experiment. The trials last 115s, and include 2 SAME trials (both directions), 4 ONE trials (all possibilities), and 10 OPPO trials (equally distributed in the two possible choices) for a total of 16 choices.

#### **Experimental conditions**

Three experimental conditions are tested during the experiment:

- Known Human Partner (KHP) : This condition is the same as HFOP from the previous experiments, renamed for clarity. The two human subjects collaborate on the task, and know that they are paired with a human. The 4C controller ensures the transfer of haptic information in the dyad.
- Hidden Human Partner (HHP) : In this condition, the subjects are told they perform the task with the virtual partner, but are actually paired with a human partner. Outside the subjects' beliefs, the rest of the parameters are identical to the KHP condition.
- Known Virtual Partner (KVP) : This condition is the same as in the previous experiment. The subjects are paired with the virtual partner and are correctly told so. The condition is further divided in multiple subconditions depending on the threshold values chosen for the virtual partner.

## Hypothesis and experimental design

The first hypothesis that will be tested in the experiment is the validity of the energy threshold metric. In order to do so, the experimental design needs to include multiple combinations of force and time thresholds which lead to the same value of energy threshold. If we observe no difference in behaviour between trials with the same values of  $E_{th}$ , while the values of  $F_{th}$  and  $t_{th}$  are different, then we can consider that the energy threshold is a good description of the underlying mechanism behind haptic negotiation. The energy threshold would thus be used in the following test as the independent variable. If on the contrary this hypothesis isn't validated, the force and time thresholds will be studied separately, as well as their interaction.

The second hypothesis is that whatever threshold is considered, increasing its value will increase the virtual partner resistance to change from Leader to Follower mode and thus increase its dominance compared to the human subjects.

The third hypothesis is that the behaviour of the subjects in human-human interaction conditions can serve as a baseline in the experimental task. The design must thus include trials in KHP condition. Moreover, in order to verify that the KHP condition is a reliable baseline, multiple trials must be included in order to verify the stability of the subjects' behaviour in human-human interaction.

The fourth hypothesis tested is that the subjects' knowledge of their partner's nature has no influence on their behaviour. This hypothesis was partly validated in the previous experiment, since no differences were found between trials where the subjects were paired with the virtual partner and knew it (KVP), and the trials where the subjects where paired with the virtual partner while thinking they were paired with a human (HVP). The reverse situation has however not yet been tested: is there a difference between trials where the humans are together and know it (KHP), and trials where the humans think they are with the virtual partner but are actually together (HHP). The HHP condition is introduced here in order to test this hypothesis.

The fifth hypothesis is that the threshold values of the virtual partner have an influence on the human behaviour on the following trial(s). For example, a subject paired with an extremely dominant partner will tend to behave in a more following fashion than his/her base behaviour in the next trials, even if the partner changes. In order to test this hypothesis, the experimental design must include transitions from all the different KVP conditions to a human-human condition. For practical reasons, all subjects won't provide data for all these transitions, and the data sets will be acquired over multiple dyads, at the cost of a reduced statistical test power. The transition will be done from KVP to HHP rather than KHP in order to prevent potential influence of the a priori on the partner's nature, if the previous hypothesis happens to be false.

The sixth hypothesis tested is that the Leader and Follower subjects in human dyads (KHP/HHP) behave differently when paired with the Virtual Partner (KVP). It is expected that different profiles of subjects lead them to behave more or less dominantly when paired together, and that these differences can also be seen in their behaviour while paired with identical Virtual Partners. More precisely, we expect that whatever the VP tuning is, subjects who tend to lead in pHHI conditions will be more dominant in pHRI conditions than their partner.

To summarize, six hypotheses are tested during the experiment:

- H1 : Energy thresholds can be linked to the dominance variations in KVP trials.
- H2 : Increasing threshold values lead to increasing VP dominance.
- H3 : The behaviour of humans in HH dyads is consistent and time invariant.
- H4 : Knowledge of the partner's nature has no influence on the human behaviour.
- H5 : Interaction with a partner of different dominance levels has lasting effects on the human behaviour.
- H6: There is a difference in dominance levels in KVP condition between subjects that were leaders/followers in HHP condition.

$T_{th}$ $F_{th}$	0.2	0.5	$T_{th}$ $F_{th}$	0.2	0.5
1.00	KVP1	KVP2	1.00	0.2	0.5
2.50	KVP3	KVP4	2.50	0.5	1.25
6.25	KVP5	KVP6	6.25	1.25	3.125

TABLE 4.10: Values of  $F_{th}$  and  $F_{th}$  for the different KVP conditions (left), and corresponding  $E_{th}$  values (right).

#### Threshold values

The experimental design includes multiple values of  $F_{threshold}$  and  $T_{th}$ . From a preliminary evaluation, thresholds values are chosen so that the difference between them is perceptible enough during the trials. Since all combinations of these thresholds must be tested in the protocol, the maximal number of threshold values must remain low, in order to keep the experiment duration acceptable. Three values of  $F_{th}$  are chosen, and two for  $T_{th}$ , for a total of 6 combinations of KVP conditions.

In order to test hypothesis H1, the experimental design needs to include force and time threshold combinations that lead to the same energy threshold. Since  $E_{th}$ =  $F_{th} \times t_{th}$ , a good way to obtain combination pairs of similar energy thresholds is to keep a constant ratio between the threshold values. The preliminary sensitivity evaluation revealed that a ratio of 2.5 was acceptable to fulfill all requirements.

The chosen threshold values and following KVP conditions are shown in Table 4.10.

#### Counterbalancing

The protocol includes 6 different combinations of thresholds values in the KVP conditions. To counterbalance the potential carryover effects, a balanced Latin square design is adopted. The balanced Latin square gives six different possible sequences of the experimental conditions, meaning the subjects will be grouped in 6 different categories. We decided to acquire two trials for each condition, and thus the Latin square sequence was repeated twice for each subject.

The KHP condition (baseline) is tested at the start and the end of the experiment, which will allow to observe potential fatigue effect, or change of behaviour during the experiment. The HHP condition is also tested twice, just after the first KHP condition. This provides data for the KHP to HHP transition, and just before the last KHP condition, which provides data for the HHP to KHP condition.

Since the second HHP trials are done at the end of the KVP tests, and since the Latin square design makes each sequence end with a different condition, all six transitions from KVP to HHP are represented in the protocol, but by different subjects. Additional precautions will be taken during data analysis to counterbalance the fact that not all subjects provide data for all conditions in this test.

#### **Final design**

The subjects are distributed in six categories, which follow a similar protocol, except for the order of the KVP conditions. Each category is tested with five subjects, for a total of 30 subjects (or 15 dyads).

The final experimental protocol is illustrated is Figure 4.11, along with the relevant hypothesis tested.



FIGURE 4.11: Experimental protocol and hypothesis tested.

## Measures

The present experiment focuses on the changes in behaviour within the dyads. The data from the experiment is analyzed from the CHOICE parts of OPPO type only, in a time window of 2 seconds centered around the path forking. In OPPO choices, the dyads members have contradictory suggested trajectories, and therefore must negotiate to reach a common agreement on the path to take (left or right). The Dominance measure is calculated as the percentage of choices "won" by a subject, that is the number of times the dyad ended up choosing his/her/its suggested trajectory, divided by the total number of choices analyzed. More complex ways of describing the dominance have been used [Groten et al., 2009, Stefanov et al., 2009] but such sophistication was not deemed necessary for our analysis.

In Human-Human dyads, the subject with the highest mean dominance across the trials is designated as the Leader, while his/her partner is referred to as the Follower. In some case, data analysis for the Leader and Follower can be done separately to search for differences in Dominance patterns.

## 4.6.4 Results

Statistical analysis of the results is performed using repeated measure (unless specified otherwise) ANOVAs when there are 3 or more values of the independent variables, and with two-tailed student t-tests otherwise. The student t-tests are corrected using Bonferonni correction. Results in the next sections are given with the following presentation: ANOVAs (F-value, p-value), t-tests (Bonferonni corrected p-value, Cohenn's d coefficient for size-effect), p-values inferior to  $10^{-4}$  are given equal to zero.

#### Consistency of Human-Human dyads behaviour

No statistical difference is found between the first and last KHP conditions (p = 0.491, d = 0.13). The results indicate that the human dyads behaviour is consistent and time invariant, hence that the KHP condition is a reliable baseline for the experiment, consistently with hypothesis H3.

## KHP vs HHP

The leader won 73% of the conflicting choices in KHP condition. The leader won 67.7% conflicting choices in the HHP condition. No significant difference is found in the dominance between KHP and HHP (p = 0.1, d = 0.4). This result reaffirms that



FIGURE 4.12: Dominance results for Leader and Follower in the different threshold conditions

prior knowledge of partner's nature has no influence in the dominance, which is consistent with hypothesis H4.

## Pertinence of the Energy threshold metric

The dominance values of the Humans and Virtual Partners for KVP of equal energy thresholds are exposed in Figure 4.12. Repeated measures t-tests are done between KVP conditions with the same energy threshold: KVP2 and KVP3 with  $E_{th} = 0.5$ , KVP4 and KVP5 with  $E_{th} = 1.25$  (see Table 4.10). No statistical difference is found between neither KVP2 and KVP3 (t = 1.09, p = 0.28), nor between KVP4 and KVP5 (t = 1.96, p = 0.06).

These results are consistent with hypothesis H1. However, the low p-value obtained for the second test, as well as the limited number of  $E_{th}$  values tested imply some caution with the conclusions of the tests. While the energy threshold is interesting, a more conservative analysis on the effects of time and force thresholds independently is also conducted.

## Influence of the thresholds values

The dominance results for the six KVP conditions can be found in Table 4.11. Two way additive ANOVA on the six KVP conditions shows a main effect force ((*F*(2, 492) = 22.8, p= 0)) and time ((*F*(2, 492) = 3.556, p = 0.04)) thresholds variations, with no interaction effect (*F*(5, 492) = 0.42, p = 0.66).

Post-hoc analysis is conducted on the effects of force and time threshold variations separately. Test data is thus aggregated for the different threshold values. The Virtual Partner dominance for each threshold value is exposed in Table 4.12. Results once again show significance for the influence of force (F(2, 492) = 22.9, P = 0) and time (p = 0.02, d = 0.34) thresholds. These results also suggest a stronger influence of the force threshold compared to the time threshold.

The virtual partner dominance significantly increases with the thresholds' values, which confirms the hypothesis H2.

## Differences between Leader and Follower dominance

Subject data is separated for Leader and Follower, and tests are performed to observe the influence of the thresholds for Leader and Follower subjects. The different dominance means are exposed in Figure 4.13.

$T_{th}$ $F_{th}$	0.2	0.5
1.00	18.3%	27.3%
2.50	33.8%	42.9%
6.25	52.3%	54.9%

TABLE 4.11: Virtual partner dominance for the different KVP conditions.

<i>F</i> <sub>th</sub>	VP dominance	$t_{th}$	VP dominance
1.00	25.1 %	0.2	36.9 %
2.50	40.7 %	0.5	43.2 %
6.25	54.3 %		

TABLE 4.12: Virtual Partner dominance for the different threshold values.

Statistical analysis shows a significant influence of the force thresholds for both the Leader (F(2,296) = 7.591, p = 0) and the Follower (F(2, 296) = 5.248, p = 0.005). On the contrary, no influence of the time threshold emerges for the Leader (p = 0.14, d = 0.29) or Follower (p = 0.97, d = 0.006).

Overall, there is a significant difference in dominance between the Leader and Follower, both in KHP (p = 0, d = 0.255), and in KVP (p = 0, d = 0.92). The subjects that are Leaders in KHP are significantly more dominant when interacting with the Virtual Partner. This is consistent with hypothesis H6.

## Lasting influence of the interaction with the VP

For this test, subject data is aggregated according to the type of the last KVP condition realized (1 to 6, see Table 4.10), with 5 subjects in each group. A one-way between-subjects ANOVA is then realized on the results in the following HHP condition, with the type of VP tuning as independent variable.

The results show no significant difference between the 6 groups (F(5, 24) = 1.016, p = 0.43), indicating that interaction with different types of Virtual Partners does not induce changes in the behaviour of the subjects on subsequent trials. This hypothesis H5 is thus invalidated.



FIGURE 4.13: Dominance results for Leader and Follower in the different threshold conditions.

## 4.6.5 Discussion

The results of the experiment show that subject behaviour is consistent across trials in human-human condition (KHP). Moreover, a priori knowledge on the partner nature doesn't seem to affect the subject behaviour (KHP vs HHP). Consequently, it can be assumed that humans exhibit an intrinsic and subject dependent tendency to dominance in negotiation situations in pHHI. It is possible that humans naturally develop and express different levels of confidence and leading behaviour, and that this behaviour is consistent throughout time. This result is consistent with research on Social Relation Model [Kenny et al., 2001], and could be validated by conducting a similar experiment while pairing the subjects in multiple dyads combinations. This was done for example in [Groten et al., 2009], where Groten et al. found that a majority of the variability in dominance in dyads was subject dependent. The fact that interaction with the Virtual Partner does not have lasting influence on the following HHP trials further confirms the consistency of human behaviour in negotiation phase.

The experimental data also shows that in pHHI, a certain imbalance exists in the dyads, as one of the subjects is systematically more dominant than the other. Additionally, humans that tend to be Leaders in pHHI condition stay more dominant in pHRI than those who tend to be followers. This means that models for Virtual Partners need to take into account the possible inter-individual variations of behaviour in order to ensure the best cooperation and thus the best performances for Human-Robot comanipulation.

Lastly, the results in the KVP conditions show that changing the force and time thresholds of the Virtual Partner modifies the subjects behaviour in reaction. This is interesting for two reasons. Firstly, it demonstrates a simple way to modulate the Virtual Partner behaviour in pHRI situation. Previous research has shown that the ability to dynamically change the role allocation is a crucial point for efficient comanipulation [Jarasse et al., 2013, Abbink et al., 2012], and changing threshold values in our model is a way to attain this result. Secondly, if it is possible to manipulate subject behaviour through changes in force and time thresholds during negotiation with the Virtual Partner, it could be possible to model that behaviour using the same thresholds. Modeling human behaviour in pHHI negotiation through a combination of time and force thresholds during interaction would allow advances in the understanding of human behaviour, and facilitate the integration of pHRI protocols.

The Energy threshold introduced in Section 4.6.2 could be used for this kind of model, as our results suggest that similar behaviour is displayed in trials involving Virtual Partners with the same energy threshold tuning for negotiation. This result suggests that humans interpret negotiation in pHHI as a biomechanical efficiency problem (cost versus performance). In this model, people each have a personal muscle energy limit that they are willing to consume to convince their partner before giving up. A precise understanding of this cost limit would allow to customize comanipulation robots to adapt to their partner in decision-making tasks. There are limitations to this assumption, since the differences between conditions of equal energy threshold almost reached significance. It is thus possible that the hypothesis would have been invalidated with another protocol, or a larger number of subjects. Further experimentations with a greater number of subjects and combinations of thresholds tested would be required to confirm the present findings. Another model combining time and force thresholds with different weights could also be tested.

## 4.7 Conclusion

This chapter presents the design and results of three experiments involving comanipulation, the first one in pHHI condition, and the following two in pHRI.

The results of the pHHI experiment further confirm the ongoing theory that humans can use the haptic channel to efficiently communicate information, and negotiate common strategies during task execution. This phenomenon remains present even after a change of scale in the task, as we used a lightweight setup, in opposition with the literature. This haptic communication allows to enhance performance in dyadic comanipulation when haptic feedback is present compared to pure visual feedback. It is also possibly the reason why dyads outperform individuals in simple coordination tasks, a common result of the literature in pHHI [Reed and Peshkin, 2008, Glynn et al., 2001, Ganesh et al., 2014, Jarasse et al., 2013]. This result is not observed in the pHHI experiment presented in this chapter, mainly due to the increased complexity of the task used. Indeed, the data analysis is focused on parts where dyads have to negotiate a common choice about the direction, which induces conflict situations, hindering the performance of the dyads compared to individuals who do not have this constraint.

Another important result of the first experiment is that initiative plays a crucial role in the negotiation for human-human dyads in comanipulation. According to the data gathered with human subjects, around 95% of the choices are won by the partner that chose to move first, even in conflicting situations. This observation led me to design a Virtual Partner based on this initiative principle, which is able to perform the task alongside a human. The second experiment was conducted to evaluate the performances of the Virtual Partner, and the behavioural differences of humans in Human-Robot or Human-Human dyads. The results of the second experiment show that the Virtual Partner performs the task successfully, without hindering the performances of the dyad nor changing the role dynamic of the partners. The subjects were in most cases unable to guess they were paired with a virtual agent instead of a human partner, and the knowledge of their partner's nature didn't affect their behaviour. These results obtained with a relatively simple state-machine algorithm are encouraging for future developments of comanipulation robots.

The third experiment was devised to further investigate the influence of the Virtual Partner on its human partner behaviour. I showed that human dominance in comanipulation can be manipulated by time and force thresholds during interaction. Moreover, data analysis of the Human-Robot dyads reveals that this dominance variation can be linked to an intrinsic and subject dependent energy threshold. This result can be interpreted as cost versus performance approach of the negotiation with muscle energy expenditure as a deciding factor. This leads to possibilities to refine current models of human-human interaction in both pHHI and pHRI.

## Part III

# Exploration of the parameters influencing kinaesthetic communication

## Chapter 5

# Influence of the teleoperation stiffness on haptic communication

## 5.1 Objective

The use of coupled haptic interfaces to recreate physical interaction has been steadily increasing in the literature, for a number of reasons discussed in earlier sections. However, no clear consensus seems to exist on the best type of controller to use, nor on which stiffness should be rendered when studying pHHI.

Melendez-Calderon et al. [Melendez-Calderon, 2011] used a rigid link to physically connect their interfaces, which guaranties an extremely high stiffness but limits the degree to which the subjects can be separated/decoupled. The solution also lacks flexibility in its tuning and only works for one degree of freedom (d.o.f) interfaces. Ganesh et al. [Ganesh et al., 2014] used two dof interfaces linked with a positionposition controller whose stiffness was set between 60 and 180 N/m. The stiffness was here purposely kept low according to the design of the experiment. Groten et al. [Groten, 2011, Groten et al., 2013] used admittance control to simulate a virtual object controlled by both subjects. The use of a high simulated mass (20kg) allows here for a high rendered stiffness(70000 N/m). Che et al. [Che et al., 2016] used two unilateral teleoperation interfaces with slave manipulators linked together via Position-Position control. Stiffness rendered are comprised between 40 and 120 N/m. De Santis et al. [Santis et al., 2014] used custom two dof arms with nonlinear admittance control over a virtual object with a rendered mass of 10kg. The forces applied on the object were the result of an elastic (stiffness 148N/m) and quadratic elastic ( $1480N/m^2$ ) stiffness components. Kucuycilmaz et al. [Kucukyilmaz et al., 2014] used admittance control to link two Phantom Premium to a virtual object whose mass isn't disclosed. The stiffness rendered here is 250 N/m and forces were limited to 4N due to the hardware. Among these studies, there is a great variability of the controller stiffness, but in most cases its maximal value is lower than 300 N/m.

High values of stiffness are however essential to accurately render the full range of haptic information. For example, it is estimated that a minimal value of 10000 N/m is needed to create the feeling of rigid contact [Lawrence and Chapel, 1994, Rosenberg and Adelstein, 1993, Hayward and Maclean, 2007]. There is however a technical cost to implement high stiffness in teleoperated haptic interfaces. Indeed, a controller able to recreate a highly rigid link between slave and master interfaces usually requires high frequency real-time hardware, and precise force sensors. There is thus a conflict between the need for stiffness and the difficulties to implement it. Given this, one could ask the question: is high stiffness necessary in teleoperation when studying pHHI ?

Some elements of answer exist in the literature: Christiansson et al. [Christiansson et al., 2008] showed that teleoperator stiffness has no influence on the ability for

subjects to discriminate the size and stiffness of various environments. Another study by Aliaga et al. [Aliaga et al., 2004] showed that in real-life implementations, better transparency of the controller increases performances in telemanipulation. Takagi et al. [Takagi et al., 2018] found a significant difference in performance between different coupling stiffnesses for a sinusoidal tracking task. To our knowledge, no other experimental study exists on the influence of quality of bilateral teleoperation control on the ability for humans to perform efficiently as a dyad in a tracking task. Moreover, no study exists on this problematic for tasks requiring common decision making through the haptic channel.

An experimental study of the influence of teleoperator stiffness on performance in pHHI is thus conducted. Two fundamental aspects of pHHI are studied: low-level interactions allowing interpersonal coordination, and high-level interactions allowing common decision-making and negotiation of strategies. These experiments will serve as a guideline for control strategies in the following experiments in the thesis.

## 5.2 Material and methods

## 5.2.1 Material

The SEMAPHORO haptic interface is used for the experiment.

## 5.2.2 Experimental conditions

Many criteria can be used to qualify the transparency of teleoperated haptic interfaces. When the interfaces are in continuous contact with an environment while a force is applied, as is the case in the study of pHHI, the most relevant criterion is the stiffness rendered by the controller [Aliaga et al., 2004]. Indeed, for fixed inertia and damping, higher transparency results in higher stiffness. The experimental validation thus focuses on the stiffness aspect of teleoperation control.

Multiple experimental conditions are tested, corresponding to controllers of different stiffness, and control conditions. The different controllers used are the following:

- No controller (ALONE) No command is sent to the interfaces; only sensors are used. Each user has visual feedback on his/her own interface position.
- Haptic Feedback from Object (HFO) No force feedback in the interfaces. Visual feedback is identical for both users and displays the median position of the two interfaces:  $X_{cursor} = (X_1 + X_2)/2$
- Position-Position with low stiffness (PPSOFT) A Position-Position (PP) teleoperation control is used. The stiffness of the link is 300 N/m, chosen as a minimal value allowing users to effectively sense the motions of the partner's interface at the scale of the task. Visual feedback is identical for both subjects.
- **Position-Position with high stiffness (PPHARD)** PP teleoperation control, with a 3000 N/m stiffness, corresponding to a stiff spring. Visual feedback is common for both subjects.
- Haptic Feedback from Object and Partner (HFOP) A four channel teleoperation scheme with adaptive gain control is implemented. The stiffness of this controller changes according to the interaction force but is comprised between 10<sup>4</sup> and 10<sup>5</sup> N/m, simulating a rigid connection between the interfaces. This condition is the same as the one used in the experiments of Part II.

 Noisy Four Channel (NOISY) Same four channels architecture as the previous condition, with an artificial Gaussian sensing noise of 0.5mm standard deviation added to the position sensors. This noise produces perceptible vibrations in the handles but does not compromise stability nor stiffness performances.

## 5.2.3 Experimental tasks

It has been proven that dyads outperform individuals in manipulation tasks where precision is required [Reed and Peshkin, 2008, Ganesh et al., 2014, Santis et al., 2014, Gentry and Feron, 2005]. These results have been observed with different setups of varying stiffnesses: from the rigidity of a physical object [Reed and Peshkin, 2008] to a soft spring-like connection [Ganesh et al., 2014]. However, it is unknown which stiffness is the best to observe the benefits of dyadic interaction. The experiments presented in this section aim at finding if the quality of the teleoperator used in pHHI studies influences their results.

The co-manipulative task that the subjects have to complete is a tracking task: a path (white line over black background) is scrolling down on their monitor, at a speed of 35mm/s. The subjects are asked to keep the position of the cursor controlled by their interfaces as close as possible to the scrolling path. In the dyadic conditions, to further incite each subject to cooperate, they are told that their goal is to maximize the common performance of the dyad. Feedback about the performance is given by the color of the cursor, which changes based on the distance between the closest path and the cursor:

- Green if  $|X_{cursor} X_{Path}| < 5 \text{ mm}$
- Yellow if  $5mm < |X_{cursor} X_{Path}| < 15 \text{ mm}$
- Red if  $|X_{cursor} X_{Path}| > 15 \text{ mm}$

The path is composed of a procedurally generated succession of curves, and its structure depends on the task. Two tasks are performed by the participants, corresponding to two separate experiments. The first task is designed to evaluate low-level haptic interactions, and requires only precision in the tracking. The second one focuses on higher level interactions, imposing that the subjects share and negotiate a common plan when confronted with a choice [Groten, 2011].

In the pure tracking task (TRAJ), the path is composed of a continuous succession of curves and straight lines. Each subpart can be a straight line, sinusoidal curve, or a right angle, imposing a "jump". The total interface workspace used for the task is 40mm wide, centered around a vertical starting position.

The high level task (CHOICE) is the same as the one used in the previous experiment and is described in Chapter 2.

At the beginning of each experiment, the subjects are explained the rationale of the setup and informed about all experimental conditions. They also run a training trial to familiarize with the setup. Afterwards, each dyad performs two blocks of 14 trials corresponding to the two experiments (TRAJ and CHOICE). The TRAJ experiment is always conducted first, followed by the CHOICE experiment. In each block, the participants perform the task twice for every experimental condition (ALONE, HFO, PPSOFT, PPHARD, HFOP, NOISY) in randomized order. Trials last for 100 s in the TRAJ block and 110s in the CHOICE one. The subjects are not informed about which conditions they are testing before each trial.

The subjects are physically separated by a curtain to prevent any visual clue about the actions of their partners, and wear audio headphones playing white noise to prevent any auditory clue (see Figure 4.1).

The study involved 32 participants (18 males, 14 females) distributed in 16 dyads (5 Male-Male, 3 Female-Female, 8 Mixed). Participants' average age was 28.8 ( $\pm$  8.7), 28 were right-handed and 4 were left-handed (left-handed participants were paired together). None had previous knowledge of the experiment or experimental set-up.

## 5.2.4 Measures

This section presents the metrics used to assess the performances of the different controllers. Like most studies in the domain of pHHI, they will cover two important aspects of comanipulation: the performance during the task (linked to the tracking precision), and the energy expenditure for the users (linked to the forces applied to the interfaces).

The first metric is a measure of the performance attained by the participants during the task. Performance for a tracking task is linked to the precision during the trial. Mean Absolute Error (MAE) is used here over Root Mean Squared Error (RMSE) since there is no need to penalize great displacements more than small ones.

MAE is calculated as:

$$MAE = \frac{1}{N} \sum_{k=1}^{N} \left| X_{\text{cursor},k} - X_{\text{target},k} \right|$$
(5.1)

with N the number of data samples,  $X_{\text{cursor},k}$  the position of the cursor at sample k, and  $X_{\text{target},k}$  the position of the path at sample k. Higher values of the MAE correspond to higher positional errors and thus lower tracking performance.

The second metric is linked to the forces used by the subjects, and the corresponding energy expenditure. Different parameters are used in the literature, each having advantages and drawbacks. The three mains approaches are to consider either the forces in the system: external and interaction forces [Stefanov et al., 2009, Feth et al., 2009b, Kucukyilmaz et al., 2014], forces applied to the interfaces [Che et al., 2016, Kucukyilmaz et al., 2014] or the energy/power flows in the system [Groten et al., 2013].

One of the experimental conditions used in the experiments artificially creates vibrations which add a lot of kinetic energy that would be calculated when using an energy or power metric for analysis. In order to fairly compare all conditions, a metric using the forces in the system is chosen. In the task presented here, the interface impedance is small compared to the user's arm impedance. Thus, the interaction forces make up most of the forces present in the system during the task. For this reason, the differences between interaction forces and total forces criteria is minimal in the present setup.

The chosen criterion will be referred as the Mean of Absolute applied Forces (MAF)

$$MAF = \frac{1}{N} \sum_{k=1}^{N} (|F_{0,k}| + |F_{1,k}|)$$
(5.2)

with  $F_{i,k}$  the force applied on the interface i at sample k. The MAF criterion represents the amount of efforts expended by the users on the interfaces during manipulation; absolute values are taken to combine both interaction forces and forces used to displace the interface. Higher values of the MAF criterion correspond to higher forces deployed by the subjects on the interfaces.

	Cond.1	AL	ONE	Н	FO	HF	FOP	PPS	OFT	PPH	ARD
	Cond.2	р	d	р	d	р	d	р	d	р	d
	HFO	1.0	-0.049	-	-	-	-	-	-	-	-
	HFOP	0.001	-0.123	0.499	-0.073	-	-	-	-	-	-
TRAJ	PPSOFT	0.0	-0.13	0.298	-0.079	1.0	-0.007	-	-	-	-
	PPHARD	0.035	-0.092	1.0	-0.042	1.0	0.029	1.0	0.036	-	-
	NOISY	1.0	-0.001	1.0	0.049	0.006	0.122	0.003	0.128	0.146	0.091
	HFO	0.0	0.648	-	-	-	-	-	-	-	-
	HFOP	0.0	0.277	0.0	-0.379	-	-	-	-	-	-
CHOICI	E PPSOFT	0.0	0.457	0.075	-0.179	0.017	0.192	-	-	-	-
	PPHARD	0.0	0.327	0.0	-0.334	1.0	0.048	0.189	-0.147	-	-
	NOISY	0.0	0.279	0.0	-0.381	1.0	-0.0	0.015	-0.193	1.0	-0.048

TABLE 5.1: p-values and Cohenn's d coefficients of pairwise comparisons of the MAE obtained for the different experimental conditions. Positive d-values indicates that performances are better in condition 1 (top), negative d-values indicates that performances are better in condition 2 (left).

	Cond.1	HFOP		PPSOFT		PPHARD	
	Cond.2	р	d	р	d	р	d
	PPSOFT	0.0	-0.155	-	-	-	-
TRAJ	PPHARD	0.337	-0.036	0.0	0.121	-	-
	NOISY	0.0	0.145	0.0	0.288	0.0	0.179
	PPSOFT	1.0	-0.014	-	-	-	-
CHOICE	PPHARD	1.0	0.043	1.0	0.054	-	-
	NOISY	0.0	0.17	0.0	0.179	0.004	0.124

TABLE 5.2: p-values and Cohenn's d coefficients of pairwise comparisons of the MAF obtained for the different experimental conditions. Positive d-values indicates that condition 2 (left) leads to higher forces applied, negative d-values indicates condition 1 (top) leads to higher forces applied.

## 5.3 Results

## 5.3.1 TRAJ experiment

## Method

One-way repeated-measures ANOVAs are performed on the data for both experimental blocks. Post-hoc pairwise t-tests are then conducted for each experimental conditions combination, and results are detailed in Table 5.1 and 5.2 for MAE and MAF respectively. MAF values for the ALONE and HFO conditions are omitted in Table 5.2 since no interaction force is taking place. Their values are kept in the figures for comparison: mean values are significantly lower compared to the teleoperated conditions because of the lightweight nature of the setup. Indeed, the interaction force is the principal source of energy expenditure in the task performed. The p-values are given after Bonferonni correction for multiple comparisons. p-values inferior to  $10^{-3}$  are given equal to 0. Cohenn's d coefficients for size effect are also precised. The sign of the d coefficients indicate which of the two compared groups has higher metric, and thus worse performance (cf legend in Table 5.1 and 5.2). For the TRAJ experiment, the metrics are calculated over the whole trials.

## MAE

A significant effect of the experimental condition on the MAE criterion is observed (ANOVA results: F(6, 10764) = 205.46, p = 0,  $\omega^2 = 0.102$ )

Post-hoc analysis shows that performances are the worst (i.e MAE was highest) respectively in the ALONE, NOISY and HFO conditions, without significant differences between them. Performances are the best for the teleoperated conditions (HFOP, PPSOFT and PPHARD), without significant differences between them. The average MAE values and standard errors can be seen on Figure 5.1a.

## MAF

A significant effect of the experimental condition on the MAF criterion is observed (ANOVA results : F(6, 10764) = 464.36, p = 0,  $\omega^2 = 0.205$ )

Post-hoc analysis shows that efforts are significantly higher (i.e MAF was higher) in the NOISY condition, and significantly lower in the PPSOFT condition. Performances for the HFOP and PPHARD are in between these extremes, without significant differences between the two. The average MAF values and standard errors can be seen on Figure 5.1b.

## 5.3.2 CHOICE experiment

#### Method

The same method as in Part 5.3.1 is applied here. Pairwise t-test results are detailed in Table 5.1 and 5.2 for MAE and MAF respectively. The values of the metrics are calculated only in the DECISION parts for the CHOICE trials. In the ALONE condition, the MAE values are calculated separately for each subject.

## MAE

A significant effect of the experimental condition on the MAE criterion is observed (ANOVA results: F(6, 2274) = 168.06, p = 0,  $\omega^2 = 0.305$ )



FIGURE 5.1: Mean values and standard errors of the MAE and MAF criterion for the two experiments.

Post-hoc analysis shows that performances are significantly lower in the HFO condition, followed by the PPSOFT condition and significantly better in the ALONE condition. Performances for the HFOP, PPHARD and NOISY conditions are in between these extremes, without significant differences between the three. The average MAE values and standard errors for the CHOICE experiment can be seen on Figure 5.1a.

## MAF

A significant effect of the experimental condition on the MAE criterion is observed (ANOVA results: F(6, 2274) = 150.93, p = 0,  $\omega^2 = 0.282$ )

Post-hoc analysis shows that efforts are significantly higher in the NOISY condition. Efforts for other conditions (HFOP, PPSOFT and PPHARD) are lower and show no significant differences between them. The average MAF values and standard errors for the CHOICE experiment can be seen on Figure 5.1b.

## 5.4 Discussion

## 5.4.1 TRAJ experiment

The first experiment consists of a pure tracking task, in which only precision and coordination are required. Different experimental conditions are tested in order to study the influence of haptic feedback and the stiffness of teleoperation controllers on the performance during the task.

The first important result of the TRAJ experiment is that the ALONE experimental condition leads to worse performances than the dyadic ones, which is a classical result in pHHI [Reed and Peshkin, 2008, Ganesh et al., 2014, Santis et al., 2014], although not observable in every scenario [Che et al., 2016]. The advantages of the dyads compared to subjects alone are however only relevant in the presence of haptic feedback (HFO is not better than ALONE). This highlights the importance of haptic communication in the success of comanipulation [Groten et al., 2013, Moll and Sallnas, 2009].

Quite predictably, the presence of mechanical noise in the system degrades the performances of the dyads. However, this decrease in precision is limited and dyads in NOISY conditions obtain performances similar to the ALONE condition, even if they use significantly more force to do so.

The most interesting result of the experiment is the fact that no significant difference in performance appears between the three teleoperation controllers. The dyads are able to outperform individuals with an equivalent margin as long as some (non noisy) haptic feedback is provided. This result seems to indicate that for comanipulative task requiring only precision (no high level decision making), the stiffness of the haptic feedback does not matter, but its quality does. The PPSOFT conditions led to lower average force applied to the interfaces compared to stiffer controllers, which may be preferable since it does not decrease the performances.

## 5.4.2 CHOICE experiment

The second experiment introduces a task requiring higher level decision making and interpersonal coordination, in the form of choices to make in the tracking task. The participants thus have to communicate their intention and negotiate a common action plan in order to succeed.

In this task, the performances are highest in the ALONE condition, since the subjects do not have to negotiate conflicting situations. Conversely, the performances are worst in the HFO condition, where the lack of haptic information decreases the negotiation possibilities. These results are in agreement with previous results from the literature [Groten et al., 2013, Roche and Saint-Bauzel, 2016].

Surprisingly, the presence of noise in the controller does not affect the performances of the dyads, as opposed to the first experiment. This would mean that higher level coordination is less affected by perturbations than low-level coordination in precise tasks.

Contrary to the previous experiment, an effect of controller stiffness is observed: the PPSOFT condition leads to significantly lower performances than the HFOP, PPHARD and even NOISY conditions. A high stiffness may thus be beneficial for comanipulative task where intention has to be communicated from one person to his/her partner.

No difference is observed in the average level of force applied by the participants in these conditions (the NOISY condition still leads to higher forces applied).

## 5.4.3 Conclusion

The results of the experiments suggest that the stiffness of the teleoperation controller does not influence performances when the task only requires individual precision and low-level interaction. On the other hand, for tasks where some communication has to take place through the haptic channel, for example to negotiate a common action plan, a higher controller stiffness leads to better performances of the dyads. These findings highlight the importance of ensuring the quality of controllers in haptic interfaces, both for study of pHHI, and later for integration of pHRI protocols, especially for task requiring high-level interaction through touch.

In [Takagi et al., 2018], Takagi et al. found a significant difference in performance between different coupling stiffnesses for a sinusoidal tracking task. Some of the stiffness values they used are similar to ours : their soft condition corresponds to our PPSOFT condition (1.7 Nm/rad vs 1.92 Nm/rad) and their hard condition was similar to our PPHARD condition (17.2 Nm/rad vs 19.2 Nm/rad). The fact that they found significant differences between these two conditions for a pure tracking task may come from the differences in setup. Their interfaces use motions from the wrist to control the individual cursor, which may be less precise than the finger used in our case. Moreover, the visual feedback provided to their subjects corresponds to the individual position of each subject, whereas we give feedback of the mean position of the dyad, which could influence the behaviour of the individuals within the dyad.

The experimental validation of the interfaces and their controller confirms the benefits of the 4C controller, especially for tasks requiring higher levels of cooperation.

## **Chapter 6**

# Sense of agency in pHHI settings

This chapter is the result of the work of many collaborators. Ouriel Grynszpan<sup>1</sup> and Ludovic Saint-Bauzel<sup>1</sup> suggested the experiment. Bruno Berberian<sup>2</sup>, Aïsha Sahai<sup>2</sup> and Elisabeth Pacherie<sup>3</sup> helped with the design of the experimental protocol, and with the writing of the article (in Cognition, submitted). Nasmeh Hamidi<sup>1</sup> and later Caroline de Goursac<sup>1</sup> supervised the experiments. I designed the experimental setup, and participated to the graphical interface design and the experiments supervision.

## 6.1 Introduction

## 6.1.1 Context

In the previous experiments, we mostly used kinesthesis related parameters to evaluate the relationships forming within the dyads. While this has led to interesting results, it may fail to encompass the subtler phenomenons happening during pHHI or pHRI. In order to go further with our study of dyadic interaction during comanipulation we turned to the field of cognitive psychology, in order to find metrics that can highlight the underlying mental mechanisms taking place when humans interact with partners.

The study of joint action is an important field of experimental psychology and neuroscience. Recent work on the subject has shown that humans are able to create mental representations of others' actions [Vesper et al., 2017], motor capabilities [Kourtis et al., 2014], and mental state [Devaine et al., 2014]. In the context of joint action, this representation is extended to a prediction of the partner's action plan [Sebanz et al., 2006], a mutual corepresentation and coprediction [Noy et al., 2011], and a blur of the separation between the actions of the self and of the partner [Kourtis et al., 2013].

Humans are able to connect on a pre-reflective level during joint action, without the need for verbal communication. But few studies have focused on the existence of this connection with virtual or robotic partners. In this chapter we adapt the work of Obhi & al. on the sense of agency in human-human and human-machine dyads in a setup allowing for more efficient haptic communication. Our objective is to determine if humans consciously or unconsciously form mental representations of virtual partners.

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FIGURE 6.1: Illustration of the intentional binding effect in voluntary actions.

## 6.1.2 Definitions

Most healthy people have the notion of the *embodied-self*, the perception that the person is one with the body. The *I-mode* is to be aware of our own actions, of ourselves, and being able to associate the results of our actions to their effects. The *we-mode*, on the other hand, is a common identity, where more than one person form a common I-mode representation together. The existence of the we-mode is a debated phenomenon, currently the subject of multiple studies in the field of psychology and neuroscience. The *joint action* in a we-mode is a collective intentionality, the capacity to co-represent others' intentions and take over their actions. And finally, *agency* is the capacity to act independently and make one's free choices.

The concept at the core of this chapter is the *sense of agency*. The sense of agency is described as the subjective, explicit, experience and judgement of "controlling one's actions, and, through them, events in the outside world" [Haggard and Chambon, 2012]. The sense of agency is currently believed to be composed of both explicit and implicit mechanisms [Synofzik et al., 2008]. The explicit sense of agency is usually captured by asking participants to judge their contribution to the action-effect. The implicit sense of agency is generally estimated using derivative phenomena such as the Intentional binding (IB) (see Figure 6.1, image from [Limerick et al., 2014]) which refers to a reduction of the perceived time between an action and its effect when the agent acted intentionally [Haggard, 2005, Haggard and Chambon, 2012]. Two types of intentions were identified: a prior intention (involving the intention to do an action at a later time) and an intention in action (involving the intention, to do an action, that immediately precedes the action itself). For an explicit sense of agency to be demonstrated, a normal flow from prior intention to intention in action is required, while for an implicit sense of agency (IB) to occur, only an intention in action is required; that is, an abnormal flow from prior intention to externally prompted action yields a different explicit judgement of sense of agency but a similar level of IB as a normal flow [Obhi and Hall, 2011a, Haggard, 2005].

## 6.1.3 State of the art

Obhi and Hall [Obhi and Hall, 2011a] have brought to light a common sense of agency (*we-agency*) when two individuals perform a common task. Nevertheless, these authors suggest in another experiment that such a common agency does not emerge when the dyad is composed of a human being and a virtual agent [Obhi and Hall, 2011b].

In their first experimentation, Obhi and Hall [Obhi and Hall, 2011a] used the general procedure of Strother et al.[Strother et al., 2010] where participants evaluated the timing of critical events that could be the results of their actions or not. Participants watched a rotating needle during each trial and estimated its position at the time of the critical events, which could be a key press (action) or a tone (effect of the action). They also estimated their feeling of causal responsibility for the critical events.

In four blocks, the key press caused a tone to occur after 200ms. Two other blocks involved pressing the space bar alone, and one last involved listening to a tone alone. Their experimental protocol consists in studying 4 conditions: judging the time of a key press alone, judging the time of a tone alone, judging the time of a key press when both a key press and a tone occur and finally judging the time of a tone when both a key press and a tone occur. In a first experiment, the participants were instructed to press the space-bar sometime between 1 and 6 seconds after the start of the clock appearance. They had to press the space-bar at their intended time unless the other participant responded first. In which case the participant had to react by immediately pressing the space-bar upon noticing that their partner had already initiated the press. This led to one partner being the initiator and the other the responder. They were instructed to balance these roles during each block. At the end of each trial, the participants had to estimate the critical event occurrence timing (position of the clock at the time of the event), and their responsibility for the critical event on a scale of 0 to 100% (0% meaning not responsible at all, 50% meaning they pressed at the same time and 100% meaning they felt entirely responsible). In a second experiment, one participant was always assigned the role of initiator and the other of responder for the entire block. The aim of this study was to determine whether IB and explicit sense of agency ratings were different between the two experiments (free role allocation versus fixed role allocation). They predicted that IB and explicit sense of agency would be stronger for initiators and expected these results would even be stronger for experiment 2 where there was no ambiguity about who initiates the action. Both their experimentation resulted in a reliable explicit sense of agency only for the initiator, although, IB was significantly demonstrated by both the initiator and the responder. Therefore, "an action need not to be freely performed to produce IB as it appears to emerge even when an action is prompted by an external event, at least in joint action contexts." When two individuals are involved in a joint action, a we-identity is formed at the pre-reflective level only and not at the conscious level.

In another paper, Obhi and Hall [Obhi and Hall, 2011b] recreated a similar experiment but introduced a virtual agent to the protocol. They used a laptop touchpad that was partnered either with another laptop touchpad used by a human, or with the computer. The participants were told that the computer was running a software replacing the other participant by simulating an action in a similar fashion. Like for the other experiment explained above, the participant had to tap the device at their own time within 5 seconds after the start of the trial. They also had to estimate the time of the critical event (the tone alone, the tap alone, the tone where both the tap and the tone occurred and the tap where both the tap and the tone occurred). In this experiment, only a partner action-interaction effect was recorded to be significant. In fact IB only emerged when the participant was paired in a joint action with another human, and no IB was observed during the baseline or with a computer partner.

## 6.1.4 Objective

One limitation of the protocol used in [Obhi and Hall, 2011b] is that no physical connection exists between the subjects, which means that the role allocation was



FIGURE 6.2: Graphical interface of the experimental setup.

purely reactive. Haptic feedback is however a crucial tool in pHRI. We believe that the addition of this haptic feedback to the protocol used to evaluate intentional binding in human-robot dyads could change the results obtained, as the subjects would have more possibilities of communication, and a better sense of telepresence.

Moreover, their setup didn't allow them to precisely determine which participant was the initiator or the follower. On the other hand, the use of haptic interfaces will allow us to record additional data on the experiments, such as velocity profiles, or interaction forces. We thus decided to adapt the protocol used in [Obhi and Hall, 2011a] and [Obhi and Hall, 2011b] to include kinesthetic feedback between the participants and their partner (human or virtual).

## 6.2 Material and Method

## 6.2.1 Experimental setup

The experimental setup is designed to reproduce the experiments of Obhi et al. with the addition of haptic communication. Instead of using a push button as an answer medium for the subjects, we use the haptic interfaces previously introduced, which allow to increase the amount of information that can be transmitted between the subjects.

As in the reference article, subjects are visually separated by a curtain, and wear headphones diffusing pink noise. The visual feedback is scraped to a minimalist graphical interface that only allows the subjects to give their answers during the experiment. An attention request is displayed at the start of the trials (Figure 6.2a), followed by a fixation cross (Figure 6.2b). Answers and feedback are given through Likert scales (Figures 6.2c and 6.2d). We decided against displaying clocks on the screen (as used in [Strother et al., 2010]) in order to reduce the cognitive load on the subject, and the number of control variables in the protocol. Likewise, the position of the haptic interfaces is not displayed during the experiment, in order to focus on the effect of haptic feedback, as suggested in [Sawers and Ting, 2014].
# 6.2.2 Virtual Partner

The Virtual Partner (VP) is programmed to randomly move rightward or leftward after a random delay between 0 and 3s. If the participant has started moving the handle before it, then the virtual partner follows her/his lead. If the VP is first to move, but the participant exerted forces in the opposite direction above a given threshold of 2N, then the virtual partner changes direction to follow the participant. This guarantees safe use for the participant. The threshold was determined empirically based on prior experimentations involving human-human interaction. The Virtual Partner motions simulate human motion using minimum jerk optimization.

# 6.2.3 Experimental conditions

## Training block : Sound-Sound delay evaluation

The first training block comprises 30 trials and is meant to provide practice in estimating time intervals. Participants receive two sequential sounds through their headphones and have to estimate the time interval separating them. They answer by moving a slider on a horizontal Likert scale (Figure 6.2c). Then, the correct interval length is displayed on another scale below their answer (Figure 6.2d, subject's answer in grey, correct answer in green). The scale extends from 0 to 2000. The interval duration between the two sounds is a random delay ranging from 300ms to 1700ms. The sounds are two different audio signals: A high-pitched beep (B6: 2000Hz) and a low-pitched beep (B5: 1000Hz). Each beep lasts 120ms. For each trial, the beginning and end sound are different. Their order of appearance randomized across trials. Each trial starts with a screen requesting for attention during 500ms (Figure 6.2a). Then, a white fixation cross over a black background appears for 2000ms (Figure 6.2b). The sequence of beep sounds is emitted 500ms after the fixation cross has appeared. When the fixation cross disappears, the Likert scale is displayed and participants are given 5s to answer. The feedback is then displayed for another 2s.

## Training block : Action-Sound association

The goal of the second training block is to instigate action-effect associative learning between the movement of the handle and the subsequent sound. This block contains 20 trials. A leftward turn of the handle is associated with the high-pitched beep and a rightward turn with the low-pitched beep. To tag the end of the handle turn, a click sound (duration 120ms) is emitted in the headphones when the handle reaches the stopper. As in the previous block, each trial starts with a request for attention during 500ms. The fixation cross then appears and the participant has up to three seconds to initiate a turn. The time interval before the beep sound appears starts when the stopper is reached. The interval duration varies randomly between 300ms and 1700ms. At the end of the trial, the handle automatically returns to its central position. The next trial can only begin when the receptor located on the handle has detected the participant's finger.

## **Baseline block : Sound-Sound test**

The baseline block comprises 40 trials and is similar to the first training block, except that (1) participants are not given any feedback about the correct interval duration, (2) the interval lasts either 700ms or 1300ms. A pseudo-random sequence is used to ensure that the number of trials is the same for either interval durations.

#### Test block : Action-Sound - Human Partner

This joint action blocks starts with a request for attention lasting 500ms, followed by the fixation cross. Once the fixation cross appears, participants have up to three seconds to turn the handles towards the stop on either side. The two participants are asked to cooperate and to equate the number of times they and their partner initiate the move. If their partner initiates the move first, they are required to follow her/his lead. For every individual trial, the role (initiator vs follower) of each co-actor is determined a posteriori when analysing the movements and forces applied on the handles. The beep sound is delivered either 700ms or 1300ms after the handle reaches the stopper, according to the same pseudo-random procedure as in the baseline block. Similarly to the associative learning block, the high-pitched beep is associated with a leftward turn and the low-pitched beep with a rightward turn. Participants then have to estimate the interval duration on a Likert scale ranging from 0 to 2000ms as in the first training block. They also have to rate on a Likert scale the degree to which they think they have contributed to causing the beep sound. They do so by moving a slider on a ruler that ranges from 0 to 100 and represents the percentage of their contribution. This block lasts for 120 trials.

#### Test block : Action-Sound - Hidden Virtual Partner

This block is the same as the human partner block, except that instead of moving their handles together, each subject is paired with the Virtual Partner during the task. This information however isn't communicated to the subjects, who are led to believe they are still paired together.

## 6.2.4 Counterbalancing

The two training blocks are always done at the beginning of the experiment, followed by the baseline and experimental blocks. The baseline and experimental blocks order are counterbalanced to prevent carry-over or learning effects.

## 6.2.5 Debriefing interviews

At the end of the experiment the two co-participants are individually interviewed to verify if they believe that they have been interacting with one another during the entire experiment. They are asked the three following questions: (1) "Do you have any comment regarding the experiment?" (2) "Did you notice a difference between the two blocks where you interacted with your partner?" (3) "In fact, you were interacting with a human partner in one block and with an automated artificial system in the other. Did you suspect that?" The answers of the participants are recorded and analysed by two independent raters. Those raters have to judge whether participants suspected that they had been interacting with a virtual partner. If the two raters disagree, the judgement of a third rater is requested. There was perfect agreement between the two initial raters for 24 participants and, of the two remaining participants, one was excluded.

## 6.2.6 Participants

Twenty-six participants (16 women) were recruited for this experiment. Before recruiting participants, we conducted a power analysis based on data reported by Obhi and Hall [Obhi and Hall, 2011a] using the G\*Power application [Faul et al., 2007] with a



FIGURE 6.3: The interval duration estimation drift from the baseline in each condition. This metric was used to assess intentional binding. It was significantly larger when the partner was human. There were no differences whether the participant was initiator or follower.

significance threshold set at 0.05 and power at 0.9. The resulting sample size estimate was 16. Participants were free of any known psychiatric or neurological symptoms, non-corrected visual or auditory deficits and recent use of any substance that could impede concentration. They were all right handed. Their mean age was 21.73 (*SD* = 3.80). This research was reviewed and approved by the institutional ethics committee. Informed consent was obtained from each participant. One participant had to be excluded, because the debriefing interview showed he had some doubts about interacting with a virtual agent. The analyses were thus based on 25 participants.

# 6.3 Results

The data was analysed using a within-subjects analysis of variances (ANOVA) with the partner (human vs VP) and the role of the participant (initiator vs follower) as factors. Given that the action-effect delay was a control variable for which we did not have any hypotheses, we did not consider it as a factor of the ANOVA and the data for the two delays (700ms and 1300ms) were aggregated. Post-hoc t-tests were conducted using Tukey's procedure.

# 6.3.1 Intentional binding and judgment of agency

Intentional binding was assessed by computing the drift of the interval duration estimation between the baseline and the operant conditions (Figure 6.3). One outlier was removed from the dataset, because her figures were always beyond two standard deviations from the mean. The analysis yielded a main effect of the partner factor (F(1,23) = 7.11, p = 0.014,  $\eta^2 = 0.24$ ). The interval drift with the human partner (*mean* = -80.6, SD = 28.8) was significantly larger than with the Virtual Partner (*mean* = -21.1, SD = 27.6). There was no other main effect or interaction. To determine in which



FIGURE 6.4: Judgement of degree of contribution in each condition. Participants rated their contribution as higher when they were cooperating with the Virtual Partner. They also judged that they contributed more when they initiated the action compared to when they followed their partner.

conditions intentional binding actually occurred, we performed a one-way ANOVA comparing interval duration estimations across every condition, that is, the baseline and the four combinations of partner and role. There was a significant main effect (*F*(4,92) = 4.27, *p* = 0.005,  $\eta^2 = 0.16$ ) (Huynd- Feldt corrected,  $\epsilon = 0.872$ ), and post-hoc tests showed significant differences with the baseline only when the partner was human, whether the participant was the initiator (*p* = 0.011) or the follower (*p* = 0.034). The difference with the baseline was not significant for the VP (*all p* > 0.85).

Regarding participants' rating of their contribution, the ANOVA indicated a main effect of the partner (F(1,24) = 12.76, p = 0.002,  $\eta^2 = 0.35$ ), and of the role (F(1,24) = 67.37, p < 0.001,  $\eta^2 = 0.74$ ) (see Figure 6.4). The participants judged their contribution as significantly higher when they were partnered with the VP (*mean* = 61.3, SD = 2.0) than with a human being (*mean* = 50.9, SD = 2.3). They also judged they contributed significantly more when they were initiators (*mean* = 63.8, SD = 1.9) than followers (*mean* = 48.3, SD = 1.8).

#### 6.3.2 Movement data

The data for the sum of interaction forces did not conform to the assumption of normality due to a floor effect, so we applied a Box Cox transformation [Sakia, 1992] to yield a normal distribution. The ANOVA for this variable showed a main effect of the partner (F(1,24) = 9.51, p = 0.005,  $\eta^2 = 0.28$ ), and a main effect of role (F(1,24) = 4.68, p = 0.04,  $\eta^2 = 0.16$ ). The average of interaction forces was significantly higher with the human partner (*mean* = 0.66N, *SD* = 0.06N) than with the Virtual Partner (*mean* = 0.50N, *SD* = 0.07N). It was also significantly higher when the participant was the initiator (*mean* = 0.60N, *SD* = 0.05N) than when she/he was the follower (*mean* = 0.60N, *SD* = 0.05N) than when she/he was the follower (*mean* = 0.60N, *SD* = 0.05N) than when she/he was the follower (*mean* = 0.60N, *SD* = 0.05N) than when she/he was the follower (*mean* = 0.60N, *SD* = 0.05N) than when she/he was the follower (*mean* = 0.60N) than



FIGURE 6.5: Sum of Interaction Forces applied by the participants. As the data was not normally distributed, boxplots were used to display the medians, the interquartile intervals and range of values in each condition. Participants applied more forces when the partner was human. When initiating action, they also applied more forces.



FIGURE 6.6: The average number of direction changes in each condition. Participants changed the direction of movement more often when the partner was human.

0.56N, SD = 0.06N). There was no interaction between the partner and role factors. Figure 6.5 shows boxplots of the data.

For the number of direction changes, we had to remove an outlier whose data was beyond two standard deviation from the mean to conform to the assumption of normality. The ANOVA yielded a main effect of the partner ( $F(1,23) = 1231.99 \ p < 0.0001 \ \eta^2 = 0.98$ ) (Figure 6.6). There were significantly more direction changes with the human partner (*mean* = 1.66 SD = 0.05) than with the VP (*mean* = 0.14 SD = 0.02).

# 6.4 Discussion

The present experiment showed dissociation between the explicit agency judgment and the implicit Intentional Binding (IB) measure, consistently with previous findings [Dewey and Knoblich, 2014]. Participants judged their contribution to the actioneffect as higher when they were paired with the Virtual Partner, while IB occurred only with the human partner and not the VP. Participants' agency judgment was also higher when they initiated joint action than when they followed it, yet there was no such difference for IB. This dissociation between agency judgment and IB in joint action had also been pointed out by Obhi and Hall [Obhi and Hall, 2011a], although a limitation of their study was that their apparatus could not discriminate who had indeed initiated the action, and thus they could not ascertain that agency judgment reliably identified the initiator and follower. Our study shows that participants had a clear perception of whether they had initiated or followed the joint action and that IB was unaffected by who was the initiator. The lack of IB when participants performed joint actions with the VP confirms the previous report by Obhi and Hall [Obhi and Hall, 2011b]. In their study, however, participants did not feel their partner's action and merely received a feedback about who had acted first once the action-effect had occurred. The joint action with a computer was created by a belief manipulation and participants were actually performing an action alone. The approach of Obhi and Hall [Obhi and Hall, 2011b] was therefore purely top-down. By contrast, participants in our experiment believed they were acting with another human while in fact it was a virtual agent. We thus opted for a bottom-up approach and nevertheless ended up with the same outcome as Obhi and Hall [Obhi and Hall, 2011b] that humanmachine joint action suppresses IB. Movement data collected via the handles might shed light on why IB was suppressed when participants interacted with the Virtual Partner. Interaction forces were higher and participants changed direction more often with the human partner than with the VP. Hence, there seems to have been some kind of standoff or negotiation taking place at the kinesthetic level between human co-actors that disappeared when the partner was a VP. This kinesthetic negotiation between co-actors might be crucial for IB to occur in the context of joint action. Such an interpretation is in line with the idea that IB is closely linked to sensorimotor processes driving the sense of agency [Synofzik et al., 2008]. More research in robotics is needed to model human-human kinesthetic joint action and the paradigm that we used here offers an adequate way to evaluate those models.

One potential limitation of the experimental setup we used was that the virtual partner only acted on the interface when moving, meaning that no other force or impedance could be felt by its partner before the motion. Therefore, the human participants could perceive (even unconsciously) a difference in behaviour between the human and virtual partners. Even though the haptic negotiation processes are certainly the main reason of the difference in IB between human and virtual partner. A simple reproduction of the human finger/hand impedance implemented in the

control of the virtual partner could be sufficient to change the results. Example of finger impedance estimation methods can be found in [Fiorilla et al., 2011, Dong et al., 2012, Bi et al., 2016].

# Chapter 7

# Is kinaesthetic communication as efficient as oral dialogue?

# 7.1 Introduction

#### 7.1.1 Context

A classical result of physical Human-Human Interaction literature is that dyads perform better than individuals during comanipulative tasks. Multiple studies have highlighted that humans also tend to take better decisions when reflecting as a team, as opposed to individuals (see [Bang and Frith, 2017], section 4 for a good overview of the literature). Teams are even better than the best team member for difficult logical tasks [Moshman and Geil, 1998]. Moreover, collective decision making has positive spillovers on individual decision making [Maciejovsky et al., 2013]. Other researchers have investigated whether dyads could outperform individuals when relying on oral communication to complete a task together.

One famous paper from Bahrami et al. [Bahrami et al., 2010] sparked the interest of the community on this problematic. In their studies, they found evidence that people are better at perceptual decision tasks when paired with a partner, if two important conditions are met: the partners must have similar level of individual sensitivities, and they should be able to communicate freely. More specifically, the level of confidence on the subjects' individual response seems to be the key factor that must be communicated in order to achieve a better combined performance. These results have later been discussed and reproduced in other studies [Koriat, 2012, Mercier and Sperber, 2012].

Knowing that communication can improve dyads performances, and that communication is proven to be conveyed through haptics, we raise the hypothesis that the results of Bahrami et al. could be reproduced when substituting verbal communication with haptic feedback between the partners. While a simple one degree-of-freedom haptic interaction is certainly unable to attain the depth and complexity of verbal communication, it may be sufficient to enable the dyads to combine their capacities and surpass individual performances.

We decided to recreate the protocol used by Bahrami et al. using the pHHI setup presented earlier. This experiment was realized in collaboration with Dr. Giovanni Pezzulo of the Institute of Cognitive Sciences and Technologies (ISTC-CNR), Roma.

## 7.1.2 Summary of the original article

The objective of the research presented in [Bahrami et al., 2010] is to understand if and how humans are able to share sensory information with others. To do so, a simple perceptual decision task is devised: dyads of subjects are shown a series of two stimuli, one of them containing an oddball target. The subjects must indicate which of the stimuli (first or second) contains the oddball target. They first answer individually, and their individual decisions are communicated to both. If the individual answers differ, the subjects are given a negotiation phase with open communication, in order to come up with a group decision. Once the group decision is submitted, feedback is given on the accuracy of the individual and group answers. The researchers propose 4 different models that could explain which kind of information is transmitted between subjects:

- the Coin Flip (CF) model considers that nothing but the decision is communicated, and that conflicts are decided by chance.
- the Behaviour and Feedback (BF) model considers that subjects learn which of them is the most accurate within the dyad, and rely on his/her choice in cases of conflict.
- the Weighted Confidence Sharing (WCS) model advances that an estimate of confidence is communicated by the subjects about their answer. Confidence is here defined as an internal estimation of the probability of being correct.
- the Direct Signal Sharing DSS model proposes that the mean and standard deviation of the sensory response of each subject is communicated to their partner.

Each model leads to a different combination of the individual sensitivities to predict the dyad sensitivity. Two experiments are used to discriminate the 4 models: one where the subjects have similar individual sensitivities, and one where noise is randomly added to the sensory signals of one subject in order to obtain dyads of very different individual sensitivities. Conclusion of the experiments is that the WCS model fits the experimental data best. Humans seem to be able to communicate their confidence while taking group decisions. In accordance with the predictions of the WCS model, two humans of similar sensitivities perform better as a dyad than alone, whereas individual of vastly different sensitivities perform worse when together.

Two additional experiments are conducted to find out if communication and/or feedback are necessary for dyads to outperform individuals in the task. In the third experiments, subjects could not communicate anything but their choice to their partner and group decision was chosen at random in case of disagreement. In the fourth experiment, the subjects could communicate but no feedback was given concerning the accuracy of their answer. Results of these additional experiments show that communication is necessary for the dyad to perform better than each individual but that feedback is not.

# 7.2 Materials and Method

## 7.2.1 Adapted protocol

In a first step, we reproduce the first experiment used by Bahrami et al. in which both subjects have the same stimuli. The experimental protocol needs to be adapted to transpose the oral communication used originally for a possibility of haptic communication.

Dyad members are in the same testing room, seated side by side in front of a computer screen (independent individual displays). An opaque curtain is positioned between them to prevent them from seeing each other. Headphones playing pink

noise are used to prevent the subjects from hearing each other or potential audio clues in the testing room. Haptic interfaces (see Chapter 3) are available for each subject to use in the relevant phases of the experiment. Visual feedback is given through individual displays. The visual interfaces are color coded for the subjects: yellow for subject 1 on the left, blue for subject 1 on the right. Subjects are instructed to refrain from trying to communicate orally with their partners for the duration of the experiment. Each experiment is divided in 1 session of 8 blocks containing 16 identical trials (the original protocol used 2 sessions, but we had to cut it in half to reduce the experiment duration to a reasonable time for the subjects). Subjects switch positions after half the trials.

Each trial proceeds as follow:

• The haptic interfaces are automatically centered, a warning message is displayed during this time (1000ms).



• A black central fixation cross is displayed on each subject's screen for a random duration (500-1000ms).



• Identical visual stimuli are then presented to each subjects (6 Gabor patches displayed in circle) twice for 85 ms. A 1000 ms pause (grey screen, black fixation cross) is observed between the two stimuli. Actual versions of the stimuli can be seen in Appendix B.



• In either the first or second stimulus, one of the 6 patches has a slightly higher contrast (oddball target).



- The objective of the subjects is to determine whether the oddball target is in the first or second stimulus.
- The oddball targets can have 4 different level of contrast compared to the baseline. The oddball target timing (first or second wave), position (one of the six patches) and contrast (one of the four levels) are randomized for each trial. The oddball timing and contrast levels were used as independent variables and the number of occurrences of each of their combinations was balanced over each block (each of the 8 combinations appears twice per block, for a total of 16 trials per block).



• After the presentation of the stimuli, the subjects must indicate their individual answer. In the reference paper, the answer is given with keyboard and mouse button press. Here, the subjects will answer by moving the handle of a haptic interface towards the left (first interval) or right (second one). In this phase, the positions of the haptic interfaces are independent, and each subject answer individually.





• After both subjects have answered, both answers are displayed for each subject. If they agree, feedback about the correct answer is given with both a color code (green for a correct answer, red for an incorrect one) and a symbol (green check mark for a correct answer, red cross for an incorrect one).



• If they disagree, only their individual choices are provided.



• In cases of disagreement, a second phase of discussion takes place in order to take a joint decision. In the reference paper, time is given to the dyad to freely discuss and negotiate towards their common decision. Here, the subjects are not

allowed to talk, but haptic feedback is added to the interfaces: the teleoperation controller will constrain the motions of the interfaces so that there are identical at all time. In this configuration, the interfaces' positions are the same and the subjects have equal control over it, additionnaly, they can feel the force applied to the interfaces by each other. The subject must jointly move the interfaces in order to indicate their final choice (left for first stimulus, right for second). The interfaces must remain one second at stop in order to validate the common answer.

MOVE YOUR INTERFACES TOGETHER TO CONFIRM YOUR ANSWER :	MOVE YOUR INTERFACES TOGETHER TO CONFIRM YOUR ANSWER :
1ST STIMULUS ? 2ND STIMULUS	1ST STIMULUS ? 2ND STIMULUS

• During the negotiation phase, a feedback about the interaction force between the interfaces is provided, in order to avoid conflicts being resolved through brute force (the subjects are asked to keep the force below the maximum).

MOVE YOUR INTERFACES TOGETHER TO CONFIRM YOUR ANSWER :	MOVE YOUR INTERFACES TOGETHER TO CONFIRM YOUR ANSWER :
1ST STIMULUS ? 2ND STIMULUS	1ST STIMULUS ? 2ND STIMULUS

• After the negotiation phase is over, feedback about the individual choices and the common decision are given to the subjects (RIGHT/WRONG).



- Each phase where feedback is given to the subjects can last a maximum of 10 seconds. A timer at the centre of the screen reflects this count.
- After 3 seconds, the subjects can bypass further wait by both placing their fingers on the interface. The contact of the finger on the interface for each subject is displayed on the screens through colored markers.
- Once the last feedback phase is completed, the graphical interface goes back to step 1, and the trials continue until the end of the experimental block.

#### 7.2.2 Data analysis method

The analysis method is taken from [Bahrami et al., 2010] (supplementary materials).

#### **Psychometric functions**

Individual and dyadic psychometric functions are constructed by plotting the proportion of trials in which the oddball target was seen in the second wave of stimuli against the contrast difference at the oddball location (contrast in the second wave minus contrast in the first). Examples of psychometric functions can be seen in Figures 7.1a and 7.1b. The dots correspond to the average proportion of 2nd choices from the experimental data, for each contrast difference ( $\pm 1,5\%, \pm 3.5\%, \pm 7\%, \pm 15\%$ ). Lines are the fitted cumulative Gaussian functions for each individuals and dyads. The psychometric curves are fit to a cumulative Gaussian function whose parameters are bias (b) and variance ( $\sigma^2$ ). Estimation of these parameters is done through curve fitting regression (Python Scipy curve\_fit() function). A participant with bias b and variance  $\sigma^2$  would have a psychometric curve given by:

$$P(\Delta C) = H\left(\frac{\Delta C + b}{\sigma}\right),\tag{7.1}$$

with  $\Delta C$  the contrast difference between second and first stimuli, and H(z) the cumulative normal function.

The psychometric curve,  $P(\Delta C)$ , corresponds to the probability of saying that the second stimulus had the higher contrast. Thus, a positive bias indicates an increased probability of saying that the second stimulus had higher contrast (and thus corresponds to a negative mean for the underlying Gaussian distribution). Given the above definitions for  $P(\Delta C)$ , the variance is related to the maximum slope of the psychometric curve, denoted *s*, via :

$$s = \frac{1}{\sqrt{2\pi\sigma^2}}.$$
(7.2)

A large slope indicates small variance and thus highly sensitive performance.

#### Weighted Confidence Sharing (WCS) Model

The data from the experiments of Bahrami et al. were best explained by the Weighted Confidence Sharing model, which considers that the participants can share their confidence in their individual answers. More precisely, the model considers that the partners take a Bayes' optimal decision based on their individual  $\delta C/\sigma$  ratios (for more details on the model construction, see the supplementary materials of [Bahrami et al., 2010]).

According to the WCS model, the dyad's psychometric function can be inferred from the individual psychometric function, as:

$$P_{dyad}^{WCS}(\Delta C) = H\left(\frac{\Delta C + b_{dyad}^{WCS}}{\sigma_{dyad}^{WCS}}\right),$$
(7.3)

with

$$b_{dyad}^{WCS} = \frac{\sigma_2 b_1 + \sigma_1 b_2}{\sigma_1 + \sigma_2} \tag{7.4}$$

and



FIGURE 7.1: Examples of psychometric functions of individuals and dyads. Dots are the average percentage of 2nd stimuli chosen as answer, for each contrast difference in the experiment. Lines are the fitted cumulative Gaussian functions. Steeper slopes correspond to higher sensitivities.



FIGURE 7.2: WCS model prediction of the dyad sensitivity compared to the ratio of members sensitivity. Dots represent the dyads examples of Figure 7.1.

$$\sigma_{dyad}^{WCS} = \sqrt{2} \frac{\sigma_1 \sigma_2}{\sigma_1 + \sigma_2}.$$
(7.5)

Consequently, the slope of the dyad's psychometric function can be calculated as:

$$s_{dyad}^{WCS} = \frac{s_1 + s_2}{\sqrt{2}}.$$
 (7.6)

According to the WCS model, the performance (sensitivity) of the dyad is superior to that of the best member if the sensitivities of the participants are similar. Indeed, if we note  $s_{max}$  the slope of the psychometric function of the best performing member of the dyad, and  $s_{min}$  the slope of his/her partner's psychometric function, we have:

$$s_{dyad} = \frac{s_{min} + s_{max}}{\sqrt{2}} = \frac{1 + \frac{s_{min}}{s_{max}}}{\sqrt{2}} s_{max}.$$
 (7.7)

If we compare the performances of the dyad to those of the best performing member we have:

$$\frac{s_{dyad}}{s_{max}} = \frac{1 + \frac{s_{min}}{s_{max}}}{\sqrt{2}} = \frac{\sqrt{2}}{2} + \frac{\sqrt{2}}{2} \frac{s_{min}}{s_{max}}.$$
(7.8)

This model is illustrated in Figure 7.2. As we can see,  $s_{dyad} > s_{max}$  if  $s_{min}/s_{max} > 1 - \frac{\sqrt{2}}{2} \simeq 0.4$ . According to the WCS model, if the ratio of sensitivities of the dyad's member is superior to 0.4 (similar sensitivities), then the dyad will outperform each individual. On the other hand, if the individual sensitivities are too different, the dyad's performance will be worse than that of the better individual.

#### First Crossing (1C) parameter

When the subjects initially disagree on the answer, a second phase takes place where they need to take a common decision. For this, they need to jointly move their interfaces towards the left or right. This joint decision making with haptic feedback is similar to the situations of conflicts (OPPO choices) in task used in Part II. It is thus interesting to see if the First Crossing parameters defined earlier can also be used in this task to predict the outcome of the common decision early.

The 1C parameter is defined as the side on which the individual position of one of the two subjects exits the interval  $[-X_{thresh}; X_{thresh}]$ . The hypothesis is that the subject that take the initiative (i.e move earlier to answer) will convince his/her partner in most cases. This relationship between initiative and leadership was strongly observed in the tracking task, and we expect to observe a similar effect in this experiment.

The position data from the common decision phase is extracted and normalised so that the middle starting position corresponds to  $X_{pos} = 0$ , and the left and right sides corresponds to  $X_{pos} = -1$  and  $X_{pos} = 1$  respectively. The value of  $X_{thresh}$  for the 1C calculations is then chosen as a percentage of  $X_{pos}$ .

#### 7.2.3 Participants

Thirty-six participants (10 women) were recruited for this experiment and paired in dyads (9 M-M, 8 M-F, 1 F-F). Participants were free of any known psychiatric or neurological symptoms, non-corrected visual or auditory deficits and recent use of any substance that could impede concentration. They were all right handed. Their mean age was 26.3 (SD = 5.25). This research was reviewed and approved by the



sensitivities ( $s_{min}/s_{max} < 0.4$ ).

(B) Dyads with members of similar sensitivities ( $s_{min}/s_{max} > 0.4$ ).

FIGURE 7.3: Average psychometric functions of the worst (blue) and best (red) individual members, compared to the dyad (black). Dots are the average percentage of 2<sup>nd</sup> stimuli chosen as answer, for each contrast difference in the experiment. Lines are the fitted cumulative Gaussian functions. Steeper slopes correspond to higher sensitivities.

institutional ethics committee. Informed consent was obtained from each participant. One dyad had to be excluded because one of the members systematically defaulted to her partner's choice in the second phase. The analysis is thus conducted on 34 participants.

# 7.3 Results

#### 7.3.1 Comparison to the WCS model

Contrary to Barhami et al., the range of sensitivities of the subjects in our experiment was quite high, so some dyads naturally had a great discrepancy in individual sensitivities, without added noise to the stimuli. The average psychometric functions of the dyads with members of different ( $s_{min}/s_{max} < 0.4$ ) or similar ( $s_{min}/s_{max} > 0.4$ ) sensitivities are exposed in Figures 7.3a and 7.3b respectively. Dyads with members of similar sensitivities were overall significantly better than the best of their members (t(13)=3.94, p<0.001). On the other hand, dyads with members of different sensitivities were significantly worse than the best member (t(4)=-9.89, p<0.0001). These results are illustrated on Figure 7.4. The significant influence of the relative dyads' members sensitivities on the dyads' performances discriminates the other models that were considered in [Bahrami et al., 2010] (CF, BF and DSS). I will thus not compare the experimental data to those models in this section, and focus on the comparison to the WCS model.

Comparing the experimental slopes of the dyads' psychometric functions to the slopes predicted by the WCS model (Equation 7.6) does not yield a significant difference (t(17)=0.51, p = 0.62). This is illustrated in Figure 7.5, where the experimental values of the dyads slopes are plotted versus their predicted values according to the WCS model.

Figure 7.6 plots the sensitivity improvement of the dyads against the relative sensitivities of their members. Each dot represents the mean data of one dyad over the 8 blocks. A linear regression model is fitted against the experimental data (green line in the Figure). A significant linear correlation is observed ( $R^2 = 0.62$ , F(1, 17) =



FIGURE 7.4: Comparison of the dyads' sensitivities to their best performing members'.

$X_{thresh}$ :	0.05	0.08	0.10	0.15	0.20	0.25	0.30
% of correct predictions :	88.5	90.0	91.9	92.9	93.7	94.6	95.7

TABLE 7.1: Proportion of dyads' choices correctly predicted by the 1C parameter.

24.8, p = 0.0002), with slope (0.64  $\pm$  0.13) and intercept (0.66  $\pm$  0.09) close to those predicted by the WCS model (0.71 for slope and intercept). The 95% confidence band is plotted in purple dotted lines.

# 7.3.2 First Crossing parameter

Multiple values of  $X_{thresh}$  are tested to observe the link between the First Crossing parameter and the final choice of the dyads in the joint decision phases. The percentage of choices correctly predicted by the 1C parameter are exposed in the Table 7.1. The 1C parameter correctly predicts more than 90% of the choices even for thresholds of less than 10% of the total motion amplitude.

# 7.4 Discussion

In the experiment presented here, pairs (dyads) of human participants performed a visual perception task. Their answers were first recorded individually, and in case of initial disagreement, they were asked to cooperate for a common answer. The subjects used the manipulation of teleoperated haptic interfaces as a mean of communication. The performances of both the individuals and the dyads were evaluated by fitting cumulative Gaussian functions to the experimental data. The maximal slope of the psychometric functions, noted *s*, is linked to the visual sensitivity for the task, and used as a performance index.



FIGURE 7.5: Experimental data of the dyads' sensitivities versus sensitivities predicted by the WCS model. Blue dots are the data points from the dyads, red line is the WCS model, green line is a linear regression model fitted on the data points.



FIGURE 7.6: Relationship between the dyads' performance compared to the relative members' sensitivity. Each blue dot represents a dyad, red line is the theoretical WCS model prediction, green line is the fitted regression linear model of the experimental data, purple dotted lines are the confidence interval on the fitted model.

The results of the experiments show that dyads perform better than their most skilled member when both individuals have similar visual sensitivities. On the other hand, when the individual members have very different sensitivities, the dyads actually perform worse on the task. These results are consistent with the results obtained in [Bahrami et al., 2010]. In this article, the researchers explain this behaviour with a model describing the choice of the dyad as a Bayes' optimal decision between subjects that are able to share their confidence levels about their individual choices when discussing.

The WCS model developed in [Bahrami et al., 2010] successfully predicts the results obtained in our experiment. However, the linear regression fit obtained from the experimental data points has a slightly lower slope than the WCS model. This could be explained by a bias towards the most skilled member during the common decision making. If we consider that the communication through haptics is less efficient than verbal dialogue, the confidence sharing could be imperfect, and subjects could try to rely on their estimate of the most skilled member, weighting his/her decision more.

According to the WCS model, the dyad sensitivity amelioration can be calculated as:  $\frac{s_{dyad}}{s_{max}} = \frac{1}{\sqrt{2}} \left(1 + \frac{s_{min}}{s_{max}}\right) = \frac{\sqrt{2}}{2} + \frac{\sqrt{2}}{2} \frac{s_{min}}{s_{max}}$  (Equation 7.8). If the dyad weights the decision of the most skilled member more, the resulting sensitivity will shift towards  $s_{max}$ :

$$\frac{s_{dyad}}{s_{max}} = \frac{\sqrt{2}}{2} + \frac{\sqrt{2}}{2} \frac{\alpha s_{min}}{\beta s_{max}},\tag{7.9}$$

with  $\beta > \alpha > 0$  the relative weights. This model would lead to a similar intercept than the WCS model, with a lower slope, which could explain the data from our experiment.

The number of experimental data points is however limited, especially for the dyads where  $s_{min}/s_{max} < 0.4$ . It would be interesting to conduct an experiment similar to the second one in [Bahrami et al., 2010], where the added noise allows to vary the sensitivity ratio between the subjects.

Regardless of this potential modification, the fact that the WCS model is the best suited to explain the results means that subjects are able to communicate through the haptic channel, and do not rely on luck or on an estimation of their performances. As a conclusion, the haptic channel is here successfully substituted to verbal communication in a pHHI task necessitating subtle common decision. Moreover, the good results obtained with the First Crossing parameters on a second experiment confirm its validity as a joint decision predictor, and the link between initiative and leadership in pHRI negotiation.

# **Chapter 8**

# **Overall conclusion and Perspectives**

# 8.1 Conclusion

The objective of this thesis was an exploratory study of physical Human-Human Interaction (pHHI), and the potential applications for the implementation of kinaesthetic communication in physical Human-Robot Interaction (pHRI). An emphasis is placed on the multidisciplinary nature of human interaction, and the resulting work is a blend of robotic design, human-robot interaction, and cognitive psychology.

A first contribution of the thesis is the design and evaluation of a novel experimental setup for the study of lightweight pHHI and pHRI. The setup is composed of two one degree-of-freedom haptic interfaces, combined with a state-of-the-art teleoperation controller allowing precision and transparency while guaranteeing stability and high-frequency force and position data acquisition. The design of this experimental setup is entirely open-source, and hopefully can be used by other researchers in the human-human or human-robot interaction community. Multiple experiments are then presented, which use the previously described setup, each concerning a different aspect of pHHI or pHRI.

In the second part, a first series of experiments is realized to investigate the effect of haptic feedback on joint decision making in a tracking task. The results firstly confirm the benefits of haptic feedback on performance. While this result is commonly seen in the literature for comanipulative tasks, it is here obtained in a lightweight environment, where the dynamics and motion ranges of the task are vastly reduced compared to the original studies. This demonstrates the reliability and robustness to changes of scale of haptic feedback benefits in pHHI context. The second and main contribution of the experiment is the observed link between initiative and leadership in negotiation during comanipulation. When confronted to a conflict during dyadic path planning, the first subject to react and take the initiative in action is almost guaranteed to take the lead and impose their choice to their partner.

Based on the data collected with human dyads, and the observed correlation between initiative and leadership, a Virtual Partner (VP) is designed, able to efficiently perform the task alongside human partners, without hindering the performances of the dyad, nor changing the role dynamic between the subjects. Further experiments are realized to evaluate the VP's performances and influence on human behaviour during interaction. The results of these experiments illustrate the efficiency of the VP in pHRI. The human-robot dyads perform the task with the same levels of performances as human-human dyads, and the subjects are generally unable to guess they are paired with a robot. The last experiment of the section proves that the leader/follower relationship within the human-robot dyads can be easily influenced by adjusting the force and time thresholds of the VP. This modification of behaviour could be implemented in cobots to modulate their tendency to leadership during task execution, through simple parameters.

In the last part, three different experiments are presented. These experiments, realized in cooperation with researchers from multiple domains, are designed to explore the interaction between human and virtual partners from a multidisciplinary perspective. The study of kinaesthetic communication is the common focus of the experiments. The results of the first experiment expose a contradiction in teleoperated haptic interfaces. In tasks requiring only shared action from the dyads, teleoperation quality (measured through the absence of noise) positively impacted the performances, while teleoperation transparency (measured through controller stiffness) did not have a significant effect. On the contrary, for task that required shared decision-making, high controller stiffness increased the performances, while teleoperation controller stiffness increased the performances of taking into account the teleoperation controller design when using teleoperated haptic interfaces for the study of pHHI.

A second experiment highlights the subconscious differences in interaction with a human or robotic partner. While human participants were unable to consciously discriminate between cooperation with a human or virtual partner, their behaviour on a subconscious level was impacted by their partner's nature. These results can probably be explained by the design of the Virtual Partner, that did not incorporate the possibility for fine kinaesthetic negotiation. While not explicitly perceptible, this difference in behaviour between the human and virtual partners was sufficient to elicit a different implicit response during the cooperation.

Finally, the third experiment confirms the efficiency of kinaesthetic communication for joint decision making. More specifically, the experiment investigates the use of kinaesthetic communication while solving a perceptual decision task. The results show that the variation in performances between individuals and dyads are similar whether subjects rely on kinaesthetic or verbal communication to take common decisions. Kinaesthetic communication, even limited to a one degree-of-freedom environment, is sufficient to efficiently share opinions and confidence levels between humans. Additionally, the correlation between initiative and leadership during decision-making was once again observed for this experiment, further validating the hypothesis.

Overall, the work of the thesis will serve as the stepping stone for future work in the field of Human-Human Interaction and the potential transfer to Human-Robot Interaction applications.

# 8.2 Perspectives

The study of physical Human-Human Interaction and its applications to physical Human-Robot Interaction is still a recent field of research, and much is left to explore and discover. The exploratory experiments realized during my thesis yielded many interesting results, but raised at least as many open questions.

This thesis has led to the birth of the Lexikhom project, which aims at inventorying haptic "words", or elemental haptic communication processes. These haptic words would be inspired from the way humans naturally use the haptic channel for communication, and implemented in cobots to reach better performances in pHRI. The Lexikhom project has multiple axes of interest for the study of pHHI, with inputs from a variety of scientific domains. The main limitation of this work, and consequently first axis of amelioration, remains the focus on one dimensional tasks. While it is a great starting point, as it greatly simplifies the design of the experimental setups, tasks and data analysis, it also limits the results to specific situations. Moreover, the generalisation from simple skill learning to complex task execution is not guaranteed [Wulf and Shea, 2002], meaning that the results obtained in the thesis may not be applicable to every situations. Transfer to an at least three dimensional setting will be required to guarantee the reliability of the work presented in this manuscript. The design of haptic interfaces with a higher number of d.o.f is therefore one of the first step of the Lexikhom project.

A promising axis for future research is the exploration of tasks which require choices in the same direction but at different distances. All of the experimental tasks used during the thesis used choices that required the subjects to move either leftward or rightward, the two being mutually exclusive. A more subtle task architecture would require subjects to make a choice by moving in the same direction but at different possible distances. Such a design could allow us to observe mechanisms like signalling highlighted in [Pezzulo et al., 2013], which is present in visuomotor tasks. Preliminary work on this aspect of pHHI can be found in Appendix C.

Another possibility of expansion of this work is to investigate asymmetrical tasks. Indeed, while the vast majority of the literature focuses on tasks where both the objective and necessary actions are equivalent for both subjects, the real-life applications of pHRI often require different roles for the two partners. This asymmetry can exist at the dyad level, with a fixed or constrained role attribution, or at the execution level, where the partners need to use different tools, or realise different subtasks. Appendix D presents an asymmetrical task that could possibly be implemented on our setup.

Lastly, collaborations with researchers from other fields are one of the most interesting perspectives. While we started this process during the thesis, I believe that the pHHI community thrives on its multidisciplinary aspect. Neuroscientists, psychologists, medical doctors, and even linguists or philosophers all have great inputs to give to the roboticists community, and the interaction with scientists from all these different domains is the most efficient way to advance our comprehension of human behaviour.

# 8.3 Publications

The work realized during this thesis has led to the following publications :

- L. Roche and L. Saint-Bauzel, "Implementation of haptic communication in comanipulative tasks: A statistical state machine model." 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Daejeon, 2016, pp. 2670-2675.
- L. Roche, F. Richer and L. Saint-Bauzel, "The SEMAPHORO Haptic Interface: a real-time low-cost open-source implementation for dyadic teleoperation", International Conference on Embedded Real-Time Systems, 2018, Toulouse
- L. Roche and L. Saint-Bauzel, "High stiffness in teleoperated comanipulation: necessity or luxury ?" 2018 International Conference on Robotics and Automation (ICRA), Brisbane
- L. Roche and L. Saint-Bauzel, "Study of haptic communication in comanipulative decision-making tasks: from human to virtual partner", Transactions on Human-Robot Interaction [SUBMITTED]

- L. Roche, A. Monachan and L. Saint-Bauzel," An experimental study of humanrobot negotiation of intentions in comanipulative tracking task", 2019 International Conference on Robotics and Automation (ICRA), Montreal [SUBMITTED]
- Ouriel Grynszpan, Aïsha Sahaï, Nasmeh Hamidi, Elisabeth Pacherie, Bruno Berberian, Lucas Roche and Ludovic Saint-Bauzel, "The Intentional Binding Suppression in Human-Robot comanipulation", Cognition [SUBMITTED]

# Appendix A

# Electronic schematic of the custom made acquisition card



# Appendix B

# **Gabor Patches Targets**

Without oddball target.

With oddball target (on the right).



# Appendix C

# Example of task with same-direction choices

# C.1 Context

Results from experimental psychology, cognitive science and neurology show that humans have the ability to infer the intentions of others from observation of their actions. Reciprocally, there is evidence that humans change their kinematic behaviour in social context, in order to facilitate this intention inference.

Becchio et al. [Becchio et al., 2008] showed that there is a difference in motion kinematics between social context and isolated execution. Georgiou et al. [Georgiou et al., 2007] showed a difference between cooperation and competitive contexts. Sartori et al. [Sartori et al., 2009] showed an influence of the need to communicate on motion kinematics. Vesper et al. [Vesper et al., 2011] observed that humans reduce their variability in dyadic compared to individual conditions. And Sacheli et al. [Sacheli et al., 2013] showed a difference between a leader and follower behaviour during task execution.

Lately, Pezzulo et al. developed the theory of *signalling*, according to which humans naturally change their motion kinematics in cooperative context in order to encode information in the trajectory. In their work, they showed that people deviated from the biomechanically optimal motion trajectories in order to facilitate the interpretation of their motions by their partner, and successfully modelled this behaviour through Bayesian Montecarlo optimisation [Pezzulo and Dindo, 2011, Pezzulo et al., 2013, Dindo et al., 2011].

While all this work was focused on visuomotor tasks, we raise the hypothesis that this behaviour can be observed in purely haptic context.

# C.2 Experimental protocol

#### C.2.1 Experimental setup

The experimental setup used for this experiment is the same as described in Chapter **3**. The mechanical stops of the handles are set closer together to reduce the maximal amplitude of motion available to the subjects (5 cm total).

#### C.2.2 Preliminary experimental task

The goal of the task is to give the subject a choice to make between two targets situated on the same side of the starting position, but at different distances. This should bring out more subtle mechanisms than targets requiring motions of opposite directions.



(A) Request to move to starting position. (B) Visual confirmation.

FIGURE C.1: At the start of each trials, subjects are prompted to move their interfaces towards the initial position.

At the beginning of each trial, the subjects are asked to move their interfaces to the starting position (see Figure C.1), and stay here. They receive visual feedback about the position of their interfaces (red line), and visual confirmation once they enter the target position (target color changes from white to green).

Once both subjects are in the starting position for more than one second, the starting zone disappears, and two target zones appears (see Figure C.2). The targets are at fixed distance, and have a fixed width. Once both subjects have reached their targets and stayed in it for one second, the trial is over and next one begins.

## C.2.3 Eliminating bias in the task

#### Motion direction

The experimental task can be designed for motions from left to right, or the opposite. These two motions can't be considered equivalent, since they require different muscle activations and thus probably have different characteristics. Two options are thus possible: include both in the protocol as a control variable, or choose one and do all trials with it, which leads to a simpler and shorter protocol. The later solution was envisioned for preliminary experiments, and all the trials are done with the starting position on the left, and targets appearing on the right.

## **Target differentiation**

The task should be designed so that no target is inherently privileged by the subjects, otherwise, the chosen target should become a dependent variable, which greatly increases the data analysis' complexity. The targets thus should be equivalent on two important points: get selected (approximatively) half the time each, and require a motion of the same "difficulty".

In [Fitts, 1954], Fitts used principles of information theory to estimate the task difficulty in (cyclic) one-dimensional reaching motions, and relate it to the average travel time. The now famous Fitts' law predicts that motion time is first order polynomial function of task difficulty:

$$MT = a + b.ID,$$
  
with  $ID = log_2\left(\frac{2D}{W}\right).$  (C.1)



(C) Targets in ONE condition.

FIGURE C.2: The experimental task : the subjects are asked to reach one of the two targets. If one target is greyed, they must privilege it, otherwise, they are free to choose. The subjects can either have the same greyed targets, or only one of them has one. ID, in bits, is the Index of Difficulty of the task, and can be obtained from the Distance (D) and Width (W) of the target.

Mc Kenzie [MacKenzie, 1992] proposed a modification of Fitts' law to better take into account the original Shannon information theory [Shannon, 1948]:

$$MT = a + b.ID = \log_2\left(1 + \frac{D}{W}\right).$$
 (C.2)

According to both of these formulations, keeping a fixed distance/width ratio yields the same task difficulty, which should be reflected in similar travel times.

A preliminary protocol was designed, and a task ID of 3 bits was chosen (see Figure C.2).

## C.2.4 Experimental conditions

Three experimental conditions are tested, similar to those in Part II:

- **Subjects separated (ALONE)**: Each subject uses their own interface and has visual feedback from their monitor about their position and virtual task. Each subject can feel their own motions and their interface's inertia, but nothing from their partner. Both subjects perform this condition at the same time independently.
- Haptic-Feedback-from-Object (HFO): In this condition, the two handles are kept free to move independently. Each subject can feel their own motions and their interface's inertia, but nothing from their partner. Each subject contributes equally to the task: the position of the cursor is identical on each screen, and computed as the mean of each handle positions:  $x_{cursor} = (x_1 + x_2)/2$ . Hence, subjects can infer the input of their partner by interpreting the movements of the cursor that are not caused by their own handle's movements.
- Haptic-Feedback-from-Object-and-Partner (HFOP): Bilateral teleoperation control is used to simulate a rigid connection between the interfaces. The positions of the handles are thus kept identical, and visual feedback about this position is given to both subjects. Additionally, the transparency of the setup allows subjects to feel the efforts applied on the interfaces by both them and their partner. The teleoperation control used guarantees that the subjects only feel their own interface's inertia, similarly to the previous conditions.

# C.3 Preliminary results

The analysis of the results showed that the travel times for the two targets were different. More importantly, the subjects had a vastly significant preference for the first target, as can be seen in Table C.1.

This imbalance shows that the task design is flawed, as the targets are not equivalent. Changes in the target parameters must be made.

# C.4 Analysis of Fitts' law for dual targets

A first series of test is realized to check if Fitts' law is verified. Subjects are asked to reach single targets from the starting zone. The targets have varying distance (D) and width (W) (4 values for each parameters). A linear correlation is observed

		Target Chosen		
		1	2	
Subject Target	None	87%	13%	
	1	96%	4%	
	2	9%	91%	

TABLE C.1: Target selection in ALONE condition, depending on which target was greyed (priority).



FIGURE C.3: Results of the Fitts' law estimation tests.

between the Motion Time and Index of Difficulty ( $R^2 = 0.59$ , F(1,794) = 1109, p = 0), suggesting that the task is indeed compatible with Fitts' law, although the correlation is less convincing than on most papers using timed cyclical tasks. These results are illustrated in Figure C.3.

Test trials are then realized with two targets of fixed distance (D) but varying width (W). A linear regression fit of Motion Time (MT) against log(W) yields different results for the two targets (see Figure C.4), confirming that a simple use of Fitts' law isn't sufficient to design the task.

Concerning the target preference, an analysis of the target choice compared to the ratio of target widths ( $W_2/W_1$ , see Figure C.5) reveals that subjects prefer the first (closest) target for similar target width, and gradually favour the second (furthest) one as the ratio increases. An equilibrium seems to be reached for a width ratio of  $W_2/W_1 \simeq 1.6$ .

# C.5 Personalised tuning of the task

Using the data from the Fitts' law tests, combined with the target preference depending on target width ratio, it is possible to obtain optimum target parameters that satisfy both conditions.

Let's begin by posing:

$$x_i = \log_2\left(W_i\right). \tag{C.3}$$

From Fitts' law, we get:

$$MT_1 = b_1 + a_1 x_1 \tag{C.4}$$



FIGURE C.4: Motion Time versus Index of Difficulty for the two targets



FIGURE C.5: Top : Repartition of the target choices compared to the target widths ratio.Middle : percentage of target 1 chosen vs target width ratio.Bottom : percentage of target 2 chosen vs target width ratio.
and

$$MT_2 = b_2 + a_2 x_2 \tag{C.5}$$

From the choice preference we get:

$$W_2 = r \times W_1 \to x_2 - x_1 = log_2(r)$$
 (C.6)

Our objective is that:

$$MT_1 = MT_2 \tag{C.7}$$

Thus we can formulate this problem as a linear system:

$$[A].X = B \tag{C.8}$$

with

$$A = \begin{bmatrix} -a_1 & 0 & 1 & 0 \\ 0 & -a_2 & 0 & 1 \\ -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 \end{bmatrix}, \quad X = \begin{bmatrix} x_1 \\ x_2 \\ MT_1 \\ MT_2 \end{bmatrix} and \quad B = \begin{bmatrix} b_1 \\ b_2 \\ log_2(r) \\ 0 \end{bmatrix}$$
(C.9)

This system has a single solution if  $det(A) = a_1 - a_2 \neq 0 \Leftrightarrow a_1 \neq a_2$ .

#### C.6 Discussion

This personalised task could theoretically leads to equal travel time and preference for the two targets. This however requires to make each subject perform a sufficient number of test trials before the actual experiments. Moreover, we need to determine how to accommodate for the different individual solutions and how to combine them for the cooperative trials.

### Appendix D

# Example of asymmetrical comanipulative task

#### D.1 Context

While most of the literature on pHHI and pHRI has focused on symmetrical experimental tasks, the applications of human-robot comanipulation mostly concern asymmetrical settings. If we take the example of rehabilitation or surgical cobots that are studied in the AGATHE team (examples in [Proietti et al., 2017, Vitrani et al., 2017, Chalard et al., 2018]), in most cases the roles accomplished by the cobot and its partner are different, albeit complementary. In this context, the study of asymmetrical comanipulation is an important topic for advances in pHRI.

Van Oosterhout et al. [van Oosterhout et al., 2018] demonstrated that dyadic cooperation led to better performances than bimanual execution on an asymmetrical assembly task.

#### **D.2** Possible experimental protocols

Using the haptic interfaces and visual feedback, a great variety of tasks can be created. Keeping the basis of a tracking task, another subtask can be added as an obstacle avoidance requirement. Such a task could represent the interaction found in automobile rallies (pilot and copilot), or in complex surgery (surgeon and interns/assistants), where the main task (following a trajectory) has to be realized with additional constraints.

Additionally, it is possible to create different subtasks by varying which kind of information is available to which participants. A baseline could consist of a symmetrical task where the subjects have information on both subtasks (tracking and obstacle avoidance), as in Figure D.1.

A first possibility of asymmetrical task can be realized by giving information to a single subtask to each subject (see Figure D.2). In this case, one subject is responsible for the tracking, and another for obstacle avoidance. The interesting parameters to observe would be how the subjects privilege their task over their partner's, when no solution can satisfy both. This repartition could be influenced by the psychological profile of the subjects, or by a predetermined role allocation, through a manipulation of the relative importance of the tasks (possibly illustrated by a scoring system).

Another asymmetrical condition can be realized with one subject having access to visual feedback about both subtasks, while the other only has access to information about one of the subtask (see Figure D.3). In such conditions, the participant with less information would be assumed to take a more following role, but could also take the role of an expert on his/her subtask, relieving the cognitive load of his/her partner.



FIGURE D.1: Baseline : symmetrical task, both subject have information about both subtasks (tracking and obstacle avoidance).



FIGURE D.2: Asymmetrical tasks 1 : each subject is responsible for one subtask.

Overall, many possibilities can be created to explore asymmetrical tasks with the use of teleoperated haptic interfaces and individual visual feedbacks. This kind of tasks are an important research thematic and need to be explored in order to fully apprehend the subtleties that need to be implemented in real-life pHRI applications.



FIGURE D.3: Asymmetrical tasks 2 : one subject has access to information about only one subtask (tracking, on the right), while the other one has access to both.

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