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# A study of haptic communication in comanipulative decision-making tasks : from human to virtual partner

Lucas Roche, *Member, IEEE*, and Ludovic Saint-Bauzel, *Member, IEEE*,

**Abstract**—This paper presents the results of an experiment on physical Human-Human Interaction (pHHI), where human dyads cooperate on a one dimensional comanipulative task. The results of this experiment confirm the existence of an haptic communication between humans during low-impedance tasks. Data from the pHHI experiment is used to design a virtual partner which can collaborate with humans on the same task. The virtual partner behavior is based on the observation that initiative is highly correlated to decision-making in pHHI. The virtual agent is then evaluated in a physical Human-Robot Interaction (pHRI) experiment. The results of the second experiment show that the virtual partner is able to perform the task without compromising the performances of the dyad, and that a similar role distribution is observed in human-human and human-robot dyads. Moreover, the knowledge of the partner's nature does not seem to influence the performances. The results obtained with the virtual partner are encouraging and could be used to design efficient haptic communication protocol in pHRI settings.

**Index Terms**—physical Human-Human Interaction, physical Human-Robot Interaction, haptic communication, comanipulation

## 1 INTRODUCTION

Since the early concept of cobots [1], significant progress in control, conception and safety has brought natural human-robot interaction closer to reality. Robotic devices have evolved from rigidly programmed entities to systems that can smoothly interact with their environment, and react to some amount of unknown parameters. Robots are now more often brought to work alongside humans and to cooperate with them for numerous tasks in a wide range of applications, from industry to health-care [2] [3]. This cooperation often leads to interaction either via direct contact, or via indirect contact through a jointly held object.

This physical Human-Robot Interaction (pHRI) brings many issues to the conception of robots [4] [2] [5] [6]. The first issue is the safety of the human user. This subject has been widely studied, both in terms of design and control of robots [7]. In addition, robots need to be able to react to unpredictable human behaviors, and 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. These two communication channel are described as "feedback" and "intent" in the framework proposed by Losey et al. [8] to describe pHRI.

Historically, the first approach towards adaptive pHRI was based on impedance control. Impedance control, introduced by Hogan [9], and extended as variable impedance control, has been used extensively as a mean to provide some flexibility in pHRI. A first study by Ikeura & al. ([10] and later [11]) used impedance control in combination with human arm impedance analysis. It was also used by Maeda et al. [12] and Corteville et al. [13] to design robotic assistants

for motion, based on minimum-jerk [14] motion analysis. Aydin et al. [15] used impedance control in combination with Kalman filters to react adaptively to human behavior. Impedance control however quickly reaches its limits since it often requires a thorough a priori knowledge on 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 [16] [17]. Role distribution changes have effectively been observed during task realization in physical Human-Human Interaction (pHHI) settings. These role exchanges are both time-varying and dyad-dependant [18] [19]. Furthermore, depending on the task, a significant role imbalance seems to be preferred : one of the partners stays more dominant than the other [18].

A lot of different solutions have been proposed in order to reproduce dynamic role exchange in pHRI, and most of them observe superior performances with dynamic role allocation than with fixed role allocation. A first approach consist in predicting human intentions in order to vary the amount of assistance given by a robotic partner. This prediction can be made by online estimation of the position or velocity of the human [15] [12] [20], or by using models of the task and human motions [21] [22]. It can also be done by using reinforcement learning algorithms to learn the task [23], or human motion primitives [24]. In all cases, the amount of leadership taken by the robot is adjusted according to the expected human behavior. Another approach uses the interaction forces as a mean to exchange information and negotiate role allocation online: Mortl et al. [25] used an analysis of redundancy in the dyad to allocate role according to the task. Oguz, Kucucyilmaz et al., Madan et al. [26] [27] [28] used force measures as a way to negotiate the amount of assistance provided in a 2D haptic board game. More unique approaches are also considered: Li et al.[29] used the minimization of a cost function linked to the task to

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modulate the robot participation, inspired by game theory. Stefanov et al. [30] 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 methods to solve pHRI complications still require to restrain the interaction to a fixed and known environment. In order to design more general pHRI control methods, a better understanding of physical Human-Human Interaction (pHHI) is needed.

The study of pHHI has already produced multiple results concerning the behavior of human-human dyads in comanipulative tasks. 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 [31] [32] [33] [34] [35] [36] [37]. Although this increase in performance may depend on the type of task [38], and the presence of force feedback between the humans [39] [40]. Simply reproducing pre-recorded human trajectories however does not yield the same benefits as interacting as a human dyad [19] [41] [33]. There seems to be a need for real-time interaction and exchange for the dyadic benefits to take place.

Interaction during pHHI is closely linked to the presence of some form of haptic or kinesthetic 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 [42] as well as an increased sense of telepresence [39] [40]. It also allows for better learning [33] [40] and performances in tracking tasks, even in cases of conflict [43]. In conclusion, many studies point at the haptic channel as an efficient mean of communication between humans [44] [45] [46] [47] [43].

If the existence of this haptic communication ability in human dyads is a well accepted theory, the precise mechanisms behind it are yet to be understood. Groten et al. [48] linked haptic communication to the energy exchanges inside the dyad, in order for the partners to negotiate between their individual motion plans. Tagaki et al. [49] advance that the Central Nervous System 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 [33] 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 has still to be understood before we can successfully replicate this ability in robots.

The aim of this paper is to evaluate the possibility of designing a virtual partner for pHRI based on models of the interactions observed in pHHI. The work presented here follows the procedure of studying pHHI to develop pHRI applications. The paper presents results obtained in pHHI experiments, that allow to link the notions of initiative and dominance. Based on these observations, a virtual agent able to behave as a partner in a human-robot comanipulative task is designed. This virtual partner is then evaluated in a pHRI experiment, and the results are discussed. All these experiments are realized on a custom made teleoperation setup using two haptic interfaces, specifically conceived for the study of lightweighted and precise comanipulative tasks.

Section 2 will present the experimental setup and protocol. Section 3 presents a pHHI experiment realized with the setup. Section 4 details the design of the virtual partner. Section 5 expose the results of the pHRI experiment evaluating the virtual agent. Lastly, section 6 draws the conclusion of the present studies.

## 2 EXPERIMENTS

### 2.1 Research questions and objectives

The first question when trying to characterize haptic communication is whether humans can actually communicate through touch, and how much does it affect performances in pHHI.

This question was explored by Groten et al. in [43]; They concluded that the presence of haptic feedback indeed enhances the precision and efficiency of human dyads in a tracking comanipulation task. The protocol used in their article is interesting for numerous reasons: Firstly, it uses a one degree of freedom (dof) interface, which allows to simplify the dynamics of the task, and maintain a greater control on the parameters influencing its execution. Secondly, the tracking task presented is continuous, as opposed to pointing or reaching tasks, which may be insufficient to highlight significant role adaptation in dyads [50]. Lastly, the task is able to induce both agreement and conflict in the dyads motion plans, allowing to explore planning in negotiation situations.

This experimental protocol is transposed to our setup for two experiments, the first one studying pHHI, and the second validating pHRI behavior. The pHHI experiment will serve two purposes: Firstly, verify that the experimental protocol yields the same results when reproduced on a setup with a much lower impedance. If so, it will both reinforce the validity of the initial hypothesis, and confirm that the interface can be properly used for the study of haptic communication. Secondly, record sensible data on pHHI that can then be used to analyze haptic communication, and design a virtual partner able to perform the task alongside a human. This virtual partner is then evaluated in the second experiment.

### 2.2 Experimental apparatus

#### 2.2.1 Context

In the study of human-human and human-robot physical interaction, three main types of setups can be considered: *Direct physical contact* seems like the most natural solution, but is generally extremely impractical for data acquisition, especially in case of force data. *Indirect physical contact through a physical object* allows to solve the problem of force data acquisition by channeling 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. Finally, *indirect contact through a virtual object*, for example using haptic interfaces and/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.

Studies in the domain of pHHI have been made using both of the later options: Reed [19] and Evrard [21] used an

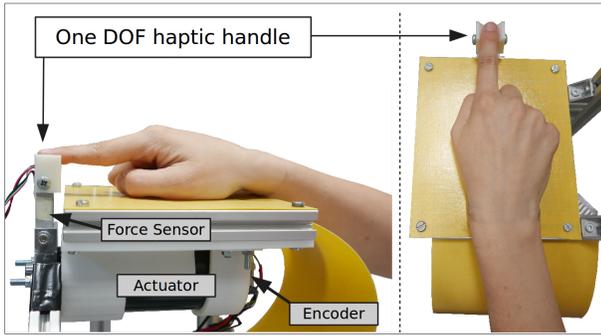


Fig. 1: The SEMAPHORO interface. A one degree-of-freedom haptic interface conceived for lightweighted and precise bilateral teleoperation.

instrumented physical object to study human-human comanipulation. Feth [43], Madan [28], Melendez-Caledron [51], or Ganesh [33] 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 guarantying stability, the high apparent impedance of these systems limits the range of tasks that can be studied. In particular, precise and lightweighted motions, which can be needed in surgery for example, cannot be studied with these high-impedance interfaces.

### 2.2.2 The SEMAPHORO Haptic Interface<sup>1</sup>

Custom-made haptic interfaces are used for the experiments presented in this paper (see Figure 1). The interfaces are designed as the support of studies on human-human and human-robot interaction, especially in the context of lightweighted and precise comanipulation tasks. The interfaces each have one rotational dof, implemented with direct drive actuation in order to minimize backlash and friction. Position and force sensors are used for data acquisition. The implementation of an optimized Four-Channels teleoperation architecture [52][53][54] allows to create a rigid virtual link between the two interfaces. When activated, this bilateral teleoperation mode allows each user to feel motions and forces applied by his/her partner through his/her own interfaces, as if both were holding the same object. Full details concerning the interfaces design and control can be found in Roche et al. [55].

### 2.2.3 Experimental Setup

The experimental setup allows two humans to use the haptic interfaces in order to perform various virtual tasks, alone or in cooperation (see Figure 2). Both participants are seated at a desk in front of a monitor (19", 1440x900p). The interfaces are placed on their right side, at an 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 headphone playing white noise during the experiment, to prevent any auditory clue.

## 2.3 Experimental task

The experiment consists in a co-manipulative task that two subjects have to complete, either alone or as a dyad.

### 2.3.1 Dyadic conditions

The experimental task 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 use the haptic interfaces described previously to control the position of a massless virtual object, represented on their screen as a cursor (see Figure 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 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. 4):

- The "BODY" category is composed of sinusoidal 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 3, 4). Considering that the subjects can neither see nor hear each other, the only way they can come to 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 [43]; 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 3):

- **SAME:** Both subjects have the same information, no conflict occurring.
- **OPPO:** Opposite information 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.

<sup>1</sup>. Système d'Évaluation de la MAnipulation Physique HOMme-RObot - System for the Evaluation of Human-Robot Physical Manipulation

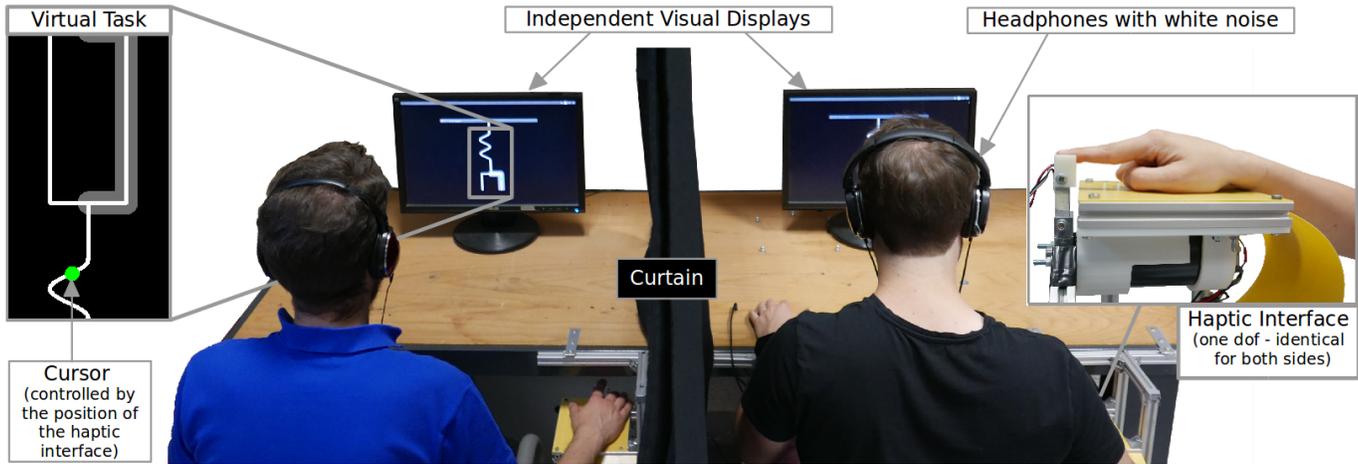


Fig. 2: Description of the experimental setup: The two participants use a one dof haptic interface to share the control over a virtual object. Visual feedback about the position of the object is given on their respective monitors as a cursor.

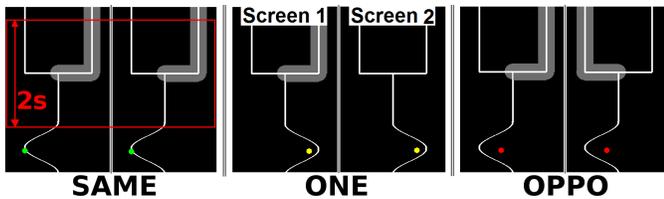


Fig. 3: Illustration of the different decision types: SAME, ONE and OPPO. Data about the choices is recorded from a 2s timezone around the path's fork (in red on the leftward figure).

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 randomized.

### 2.3.2 Individual conditions

In the individual conditions, the overall task is kept 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 direction at random in the case they don't.

## 2.4 Experimental conditions

The two experiments presented in this paper use the same experimental task. The first experiment aims at studying the behavior of human-human dyads in a comanipulative one degree of freedom task. The second experiment aims at evaluating the performances of a virtual partner in human-robot dyads on the same task. Five different experimental conditions are used across the two experiments:

- **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

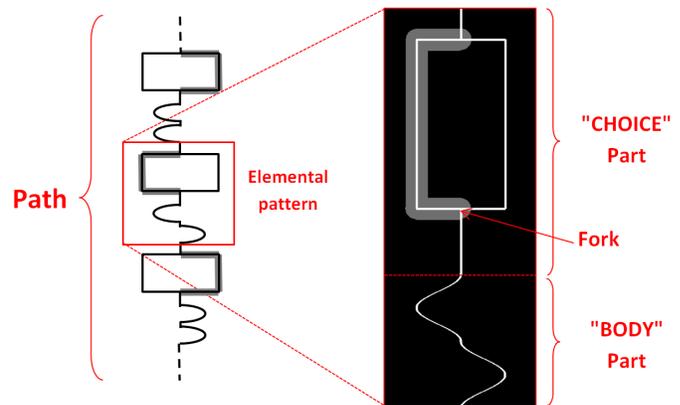


Fig. 4: Illustration of the experimental task. A pattern composed of sinusoidal parts (BODY) and a fork (CHOICE) is repeated 15 times to create each trial. The orientation of the parts is randomly generated.

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 tele-

operation control used guarantees that the subjects only feel their own interface's inertia, similarly to the previous conditions.

- **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 part 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 behavior of the human subjects depending on their a-priori about their partner.

## 2.5 Metrics

### 2.5.1 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):

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

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  $RMS_{max}$ :

$$Performance = 1 - \frac{RMS}{RMS_{max}} \quad (2)$$

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

### 2.5.2 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 by Groten&al. in [43] is chosen for this measure. It is defined as the sum of absolute values of the power flows from the subjects to their interfaces:

$$MAP = MAP_1 + MAP_2 = \frac{1}{N} \sum_{k=1}^n |P_{1,k}| + \frac{1}{N} \sum_{k=1}^n |P_{2,k}| \quad (3)$$

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

### 2.5.3 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.

$$DOM_s = \frac{n_{s,win,OPPO}}{n_{OPPO}} \quad (4)$$

where  $s = 1, 2$  designs 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 overall dominance across the experiment. Levels of dominance are investigated for all experimental conditions.

## 3 HUMAN-HUMAN HAPTIC COMMUNICATION EVALUATION

### 3.1 Protocol

Three different experimental conditions are tested in this experiment, in order to study the influence of the presence of haptic feedback on the performances in a comanipulative task: ALONE, HFO and HFOP.

Each dyad starts the experiment 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. 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:

$$\begin{array}{l} \text{a) } \boxed{ALONE(\times 2) \mid \frac{HFO(\times 2)}{HFOP(\times 2)} \mid ALONE(\times 2) \mid \frac{HFOP(\times 2)}{HFO(\times 2)}} \\ \text{b) } \boxed{ALONE(\times 2) \mid \frac{HFO(\times 2)}{HFOP(\times 2)} \mid ALONE(\times 2) \mid \frac{HFOP(\times 2)}{HFO(\times 2)}} \end{array}$$

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 y). All participants were right-handed and had no previous knowledge of the experiment or the experimental set-up. Each dyad provided data for every experimental condition.

### 3.2 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 are studied for each combination of Experimental Condition and Decision Type. Data is analyzed over a 2s window around the Choice (see Figure 3). Data from all trials are used except for the first bloc 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 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. [31] and Che et al. [38] used paired sample t-tests. Feth et al. [48], Van der Wels et al. [46] and Mireles et al. [56] used repeated measures ANOVA. Other articles used ANOVA without precision of the design considered [36][33].

The statistical analysis is here performed with repeated measures two-ways ANOVA, 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 form: 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.

#### 3.2.1 Learning effect

The experimental design used for this experiment is not entirely counterbalanced : all dyad conditions are tested after an individual trial, but not always after the same number of total trials. This poses a risk for the statistical analysis if a learning effect is observed between the different trials. One-way repeated measure ANOVA does not show any significant effect of the trial number on the performances in any experimental condition (ALONE :  $F(3, 60) = 1.38, p = 0.25, \omega^2 = 0.004$  ; HFO :  $F(1, 30) = 0.17, p = 0.73, \omega^2 = 0.001$  ; HFOP :  $F(1, 30) = 2.06, p = 0.15, \omega^2 = 0.013$ ). Moreover, performance isn't significantly affected by the order of the experimental condition : Student's t-tests, HFO first vs HFOP first (HFO :  $p = 0.33, d = 0.01$ ; HFOP :  $p = 0.53, d = 0.04$ ).

#### 3.2.2 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 5.

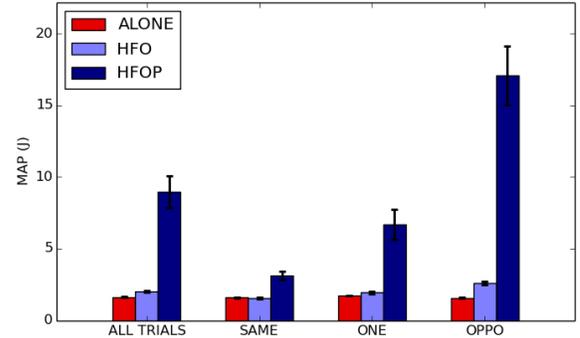


Fig. 5: MAP parameter results for the pHHI experiment. (Error bars represent standard errors of the distributions.)

The differences in performance are described in tables 1 and 2. Details of the t-tests are omitted for clarity, significant differences with a p-value inferior to 0.05 are signaled with a (\*), p-values inferior to 0.001 are signaled with a (\*\*).

TABLE 1: Influence of the Decision Type over MAP criterion depending on the Experimental Condition

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	<i>SAME &lt; ONE*</i>	<i>SAME &lt; OPPO**</i>	<i>ONE &lt; OPPO**</i>
HFO	<i>SAME &lt; ONE**</i>	<i>SAME &lt; OPPO**</i>	<i>ONE &lt; OPPO**</i>
ALONE	<i>SAME ~ ONE</i>	<i>SAME ~ OPPO</i>	<i>ONE ~ OPPO</i>

TABLE 2: Influence of the Experimental Condition over MAP criterion depending on the Decision Type

Type	ALONE vs HFOP	ALONE vs HFO	HFOP vs HFO
SAME	<i>ALN &lt; HFOP**</i>	<i>ALN &lt; HFO**</i>	<i>HFOP &gt; HFO**</i>
ONE	<i>ALN &lt; HFOP**</i>	<i>ALN &lt; HFO**</i>	<i>HFOP &gt; HFO**</i>
OPPO	<i>ALN &lt; HFOP**</i>	<i>ALN &lt; HFO**</i>	<i>HFOP &gt; HFO**</i>

#### 3.2.3 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 3 and 4. Details of the t-tests are omitted for clarity, significant differences with a p-value inferior to 0.05 are signaled with a (\*), p-values inferior to 0.001 are signaled with a (\*\*).

TABLE 3: Influence of the Decision Type over Performance depending on Experimental Condition

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	<i>SAME ~ ONE</i>	<i>SAME &gt; OPPO*</i>	<i>ONE &gt; OPPO*</i>
HFO	<i>SAME &gt; ONE**</i>	<i>SAME &gt; OPPO**</i>	<i>ONE &gt; OPPO**</i>
ALONE	<i>SAME ~ ONE</i>	<i>SAME ~ OPPO</i>	<i>ONE ~ OPPO</i>

TABLE 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 ~ HFO
ONE	ALN > HFOP**	ALN > HFO**	HFOP > HFO*
OPPO	ALN > HFOP**	ALN > HFO**	HFOP > HFO**

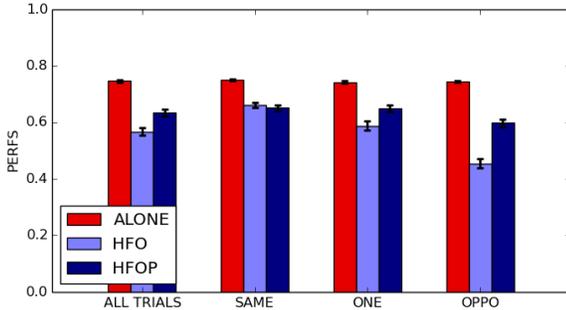


Fig. 6: PERFS parameter results for the pHHI experiment. Error bars represent standard errors of the distributions.)

### 3.2.4 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.

## 3.3 Discussion

The first experiment aims at illustrating differences in performances and interaction force 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 results 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 [57], the same experimental setup was 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 necessary 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 results 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, 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.

Some differences in results are found between this study and Groten et al. [43]: for the MAP criterion, a greater difference between the HFO and HFOP conditions is found in the present study, as well as a significant difference between the SAME and ONE decision types. For the performance criterion, the present study found significant differences between decision types in HFOP while none were found in [43]. These differences could be explained by the change of scale in the experimental apparatus, leading to a different repartition between the efforts used for the task and those used for communication.

The main results, namely that the addition of haptic feedback in comanipulative tasks leads to greater efforts and performances, are however consistent with [43], while obtained with a different experimental apparatus. This reinforces the hypothesis that humans can indeed communicate via a haptic communication channel. Moreover, this communication seems to be present in tasks involving varying impedance and forces.

Overall, the decision making was heavily biased in favor 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, the other participant acting like a "Follower". This dominance discrepancy is in agreement with previous results [18] and was more pronounced in the HFOP condition than the HFO condition, which could be explained once again by the higher amount of information available for negotiation, helping the leader cement his role more easily.

## 4 VIRTUAL PARTNER DESIGN

This section presents the design of a virtual agent that will be used in a pHHI scenario. The partner should be able to

perform the task alongside a human, without hindering his performance, and without taking full control of the task.

In order to design this virtual partner, data from the Human-Human experiment presented in Part 3 is analyzed to identify repeatable characteristics of the human behavior 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 on-line and react accordingly. In the following paragraphs, such a variable will be called *online predictor*.

#### 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 done on the acceptable accuracy and duration of the detection phase.

The principal constraints for the choice of the predictor are its accuracy, the computing duration, and the online nature of the detection. The need for accuracy is obvious if the objective is to react correctly to human behavior. 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 chose 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 [58]).

#### 4.2 Definitions

Each CHOICE Phase (see part 2.2.3) 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 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  $0 \leq t_{start} < t_{stop} \leq t_{choice} = 1$  (see Figure 7). 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  $X_{max} = 80 \text{ pixels} \simeq 24 \text{ mm}$ .

#### 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

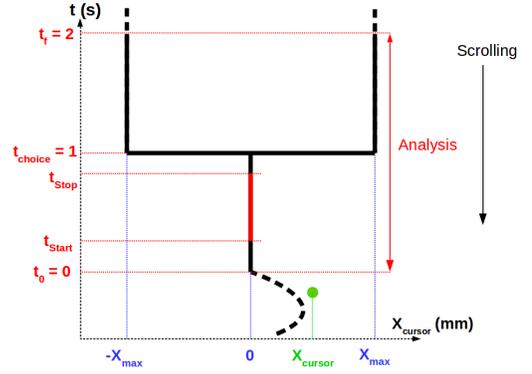


Fig. 7: Presentation of the CHOICE part and associated variables.

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 Online Predictors

In order for the predictors to be implemented in the virtual agent behavior, 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 interface 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 [28] or [30].

##### 4.4.1 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  $t_{stop}$ .
- $V_M = \sum_{k=1}^N \frac{\dot{X}_{cursor}(k)}{N}$  : 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  $[t_{start}; t_{stop}]$ .

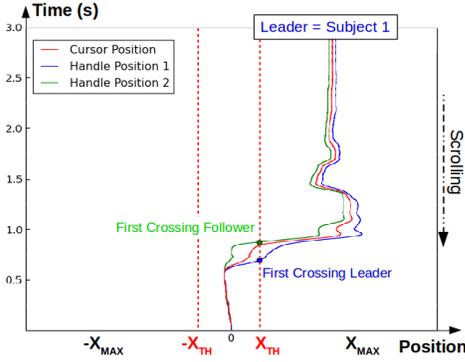


Fig. 8: The First Crossing parameter is defined as the side on which the individual position of a subject first drifts from the central position of 35% of the total target distance. Position difference between subjects is exaggerated for clarity.

#### 4.4.2 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 8.

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. The results show that accuracy indeed increase for a later beginning of the analysis. Similarly, increasing the threshold size allows to increase the accuracy of the prediction, since a wider motion need to be made to trigger the First Crossing detection.

If a larger threshold size leads to better performances, it however leads 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 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 starting at 0.2 second.

#### 4.5 Accuracy of the predictors

Figure 9 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 analyzed 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

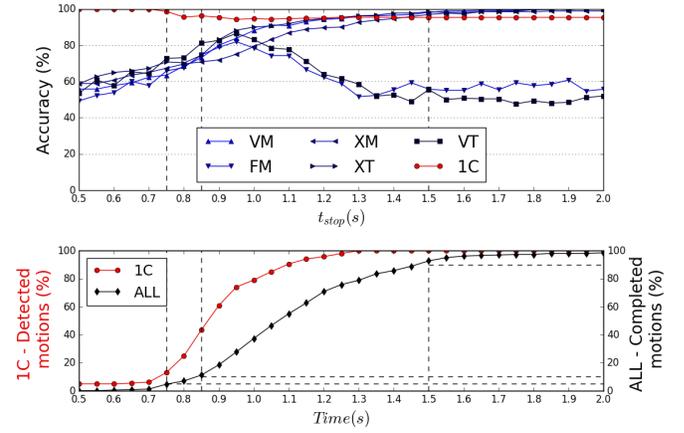


Fig. 9: Top: Accuracy of the different predictors as a function of the analysis end time. Vertical dotted lines represent the time at which 5%, 10% and 90% of the motions are completed, predictor accuracies for these times can be found in table 5.

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.

the motions are already completed (see Figure 9, bottom), meaning that while accurate, the prediction will be obtained too late in most of the 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 proportions 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 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 9, bottom). Indeed, the  $X_{thresh}$  of the 1C predictor is always crossed before the motion 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.

Accuracy at 0.75s (5% of motions ended)	Accuracy at 0.85s (10% of motions ended)	Accuracy at 1.5s (90% of motions ended)
<b>1C</b> 98.57%	<b>1C</b> 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%	<b>1C</b> 95.29%
FM 65.77%	VM 73.07%	FM 55.77%
VM 63.46%	XM 70.77%	VT 55.38%

TABLE 5: Accuracy of the predictors at different times during the Choice Phase.

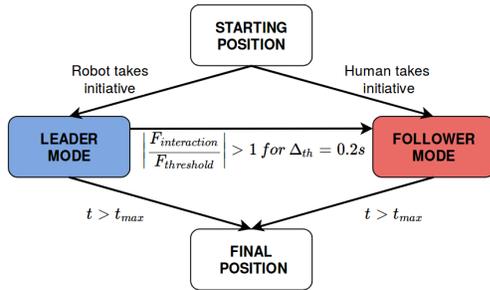


Fig. 10: Schematic of the algorithm. The algorithm is designed to let the human lead the movement as a default choice. In the absence of human initiative, the virtual partner engage the movement toward its own target.

#### 4.6 Virtual Partner Design

The previous findings are used to design an algorithm which can reproduce the observed behavior, 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 10) is designed to model human behavior. 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 its own handle).

In the BODY parts, the algorithm follows the path. When confronted to a CHOICE, the algorithm generates a minimum-jerk trajectory [14] 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 behavior 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 ( $\mathcal{N}(1.1, 0.1)$ ).<sup>2</sup>

Two situations are then possible: if the human takes initiative<sup>3</sup> before the starting time of the virtual partner, it

2. The trajectories generated by the virtual agent are not perfect with regards to the execution of the task (precise tracking of the target). This is done intentionally so that the performances of the virtual agent do not influence the behavior of the human partner during the task.

3. Taking the 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.

lets the human lead, entering "Follower Mode". The virtual partner generates a new trajectory to reach the chosen path. 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", and starts 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. 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). A force threshold  $F_{threshold} = \pm 1N$  is chosen according to the experimental data. As for the interaction force measured, the force threshold sign is positive if the virtual object is on the left, and negative on the right. If this interaction force exceed the force threshold for a duration of  $\Delta t_h = 0.2s$  (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.

## 5 2ND EXPERIMENT - PHRI

### 5.1 Protocol

The second experiment uses four experimental conditions, designed to evaluate the performances of the virtual partner, and the influence of a priori knowledge on the nature of this partner. Preliminary results have already been presented [59]. This previous study used another haptic interface with limited capabilities and no force sensors. Tests using the new interfaces are thus conducted to assess the validity of the previous results. Moreover, a new experimental condition is added in order to differentiate the cases where the participants were aware or not of the nature of their partner. The task and experimental set-up are similar to those exposed in the previous section, with only the experimental conditions changing. The participants are the same as in the previous experiment.

The experimental conditions tested are ALONE, HFOP, HVP and KVP.

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 (×2)	HFOP(×2) ----- HVP(×2)	ALONE (×1)	HVP(×2) ----- HFOP(×2)	ALONE (×1)	KVP (×2)
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The order between HFOP and HVP is randomized, and the ALONE condition is tested between these two, in order 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, in order to avoid a potential influence on their behavior during the other conditions.

## 5.2 Results

The results of the second experiment are exposed in this section. 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 Part 3.2.

### 5.2.1 Learning effect

The experimental design used for this experiment is not entirely counterbalanced : all dyad conditions are tested after an individual trial, but not always after the same number of total trials. This poses a risk for the statistical analysis if a learning effect is observed between the different trials. One-way repeated measure ANOVA does not show any significant effect of the trial number on the performances in any experimental condition (ALONE :  $F(3, 60) = 1.38, p = 0.25, \omega^2 = 0.004$  ; HFOP :  $F(1, 30) = 2.06, p = 0.15, \omega^2 = 0.013$  ; HVP :  $F(1, 30) = 1.02, p = 0.36, \omega^2 = 0.0001$  ; KVP :  $F(1, 30) = 0.27, p = 0.61, \omega^2 = 0.004$ ). Moreover, performance isn't significantly affected by the order of the experimental condition : Student's t-tests, HFOP first vs HVP first (HFOP :  $p = 0.45, d = 0.021$ ; HVP :  $p = 0.62, d = 0.015$ ).

### 5.2.2 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 6 and 7. Details of the t-tests are omitted for clarity, significant differences with a p-value inferior to 0.05 are signaled with a (\*), p-values inferior to 0.001 are signaled with a (\*\*).

TABLE 6: Influence of the Decision Type over MAP

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	<i>SAME &lt; ONE*</i>	<i>SAME &lt; OPPO**</i>	<i>ONE &lt; OPPO**</i>
HVP	<i>SAME &lt; ONE**</i>	<i>SAME &lt; OPPO**</i>	<i>ONE &lt; OPPO**</i>
KVP	<i>SAME &lt; ONE**</i>	<i>SAME &lt; OPPO**</i>	<i>ONE &lt; OPPO**</i>
ALONE	<i>SAME = ONE</i>	<i>SAME = OPPO</i>	<i>ONE = OPPO</i>

TABLE 7: Influence of the Experimental Condition over MAP

Dec. Type	ALONE vs HFOP	ALONE vs HVP	ALONE vs KVP
SAME	<i>ALN &lt; HFOP**</i>	<i>ALN &lt; HVP**</i>	<i>ALN &lt; KVP**</i>
ONE	<i>ALN &lt; HFOP**</i>	<i>ALN &lt; HVP**</i>	<i>ALN &lt; KVP**</i>
OPPO	<i>ALN &lt; HFOP**</i>	<i>ALN &lt; HVP**</i>	<i>ALN &lt; KVP**</i>
Dec. Type	HFOP vs HVP	HFOP vs KVP	HVP vs KVP
SAME	<i>HFOP &gt; HVP**</i>	<i>HFOP &gt; KVP**</i>	<i>HVP &lt; KVP**</i>
ONE	<i>HFOP &gt; HVP**</i>	<i>HFOP &gt; KVP**</i>	<i>HVP ~ KVP</i>
OPPO	<i>HFOP &gt; HVP**</i>	<i>HFOP &gt; KVP**</i>	<i>HVP &lt; KVP**</i>

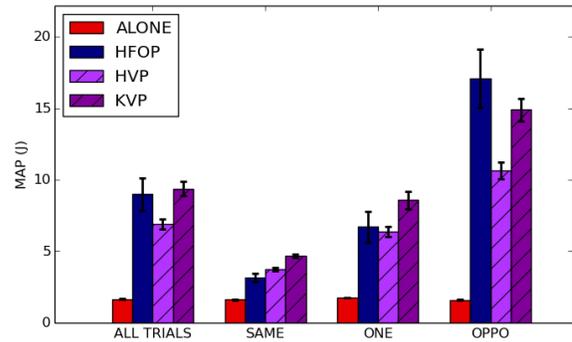


Fig. 11: MAP parameter results for the pHRI experiment. Error bars represent standard errors of the distributions.)

### 5.2.3 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 8 and 9. Details of the t-tests are omitted for clarity, significant differences with a p-value inferior to 0.05 are signaled with a (\*), p-values inferior to 0.001 are signaled with a (\*\*).

TABLE 8: Influence of the Decision Type over Performance depending on Experimental Condition

Condition	SAME vs ONE	SAME vs OPPO	ONE vs OPPO
HFOP	<i>SAME ~ ONE</i>	<i>SAME &gt; OPPO*</i>	<i>ONE &gt; OPPO*</i>
HVP	<i>SAME &gt; ONE**</i>	<i>SAME &gt; OPPO**</i>	<i>ONE &gt; OPPO**</i>
KVP	<i>SAME &gt; ONE**</i>	<i>SAME &gt; OPPO**</i>	<i>ONE &gt; OPPO**</i>
ALONE	<i>SAME ~ ONE</i>	<i>SAME ~ OPPO</i>	<i>ONE ~ OPPO</i>

TABLE 9: Influence of the Experimental Condition over Performance depending on Decision Type

Dec. Type	ALONE vs HFOP	ALONE vs HVP	ALONE vs KVP
SAME	<i>ALN &gt; HFOP**</i>	<i>ALN ~ HVP</i>	<i>ALN &gt; KVP**</i>
ONE	<i>ALN &gt; HFOP**</i>	<i>ALN &gt; HVP**</i>	<i>ALN &gt; KVP**</i>
OPPO	<i>ALN &gt; HFOP**</i>	<i>ALN &gt; HVP**</i>	<i>ALN &gt; KVP**</i>
Dec. Type	HFOP vs HVP	HFOP vs KVP	HVP vs KVP
SAME	<i>HFOP &lt; HVP**</i>	<i>HFOP &lt; KVP**</i>	<i>HVP ~ KVP</i>
ONE	<i>HFOP ~ HVP</i>	<i>HFOP ~ KVP</i>	<i>HVP ~ KVP</i>
OPPO	<i>HFOP ~ HVP</i>	<i>HFOP ~ KVP</i>	<i>HVP ~ KVP</i>

### 5.2.4 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

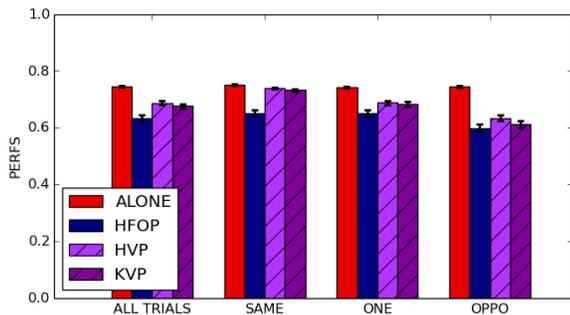


Fig. 12: PERFS parameter results for the pHRI experiment. Error bars represent standard errors of the distributions.)

paired with the virtual partner (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 ( $p < 0.001$ ,  $d = -1.82$ ).

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.

### 5.2.5 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	( $\pm$ )Std
Alone	0.746	0.067
ROBOT	0.721	0.110
HVP	0.688	0.145
KVP	0.676	0.157
HFOP	0.633	0.141

## 5.3 Discussion

In the second experiment, a virtual partner is designed based on the observation of human behavior during decision making tasks in physical Human-Human interaction. The virtual partner is then tested 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 with human partners, even in conflicting situation. Indeed, the performances in the HVP and KVP conditions are always equal or superior to the performances in HFOP condition. Furthermore, this results does not come from higher performances of the robot guiding or leading the human, since the robot alone reaches performances similar to humans alone, and the distribution of decision leading (Dominance) was 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.

A limitation of this 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 results: human participants that tend to be Leader in HFOP condition stay overall Leaders in the HVP condition (although it is less pronounced). Likewise, Followers in HFOP behave the same when unknowingly paired with the robot (once again less pronounced). We hypothesize that the Leader/Follower behavior of humans can be modeled by an intrinsic time/force threshold for negotiation, which varies for each person. The behavior in HVP could be explained by the fact that our tuning of the thresholds happen to be slightly lower to those of a Leader personality, but higher than those of a Follower personality. Similarly, the more dominant behavior of humans in KVP condition could be explained by humans having higher thresholds if they know their partner is robotic, and/or if they are more confident in the task. If this hypothesis is true, it should be possible to influence the behavior of partners in human/robot dyads by controlling the time/force thresholds available for negotiation. Exploration of this hypothesis will be the subject of a future study.

## 6 CONCLUSION

This paper presents the results of an experiment on physical Human-Human Interaction (pHHI), where human dyads cooperate on a one dimensional comanipulative task. The results of this experiment confirm the existence of an haptic communication between humans during low-impedance tasks. Data from the pHHI experiment are used to design a virtual partner which can collaborate with humans on the same task. The virtual partner behavior is based on the observation that initiative is highly correlated to decision-making in pHHI. The virtual agent is then evaluated in

a physical Human-Robot Interaction (pHRI) experiment. The results of the second experiment show that the virtual partner is able to perform the task without compromising the performances of the dyad, and that a similar role distribution is observed in human-human and human-robot dyads. Moreover, the knowledge of the partner's nature does not seem to influence the performances. The results obtained with the virtual partner are encouraging and could be used to design efficient haptic communication protocol in pHRI settings.

The virtual partner seems to be able to successfully reproduce human behavior, both in terms of performances and decision making. Moreover, no participant declared having detected differences between HVP and HFOP conditions, when asked in post-experiment interviews. The fact that a simple state-machine algorithm can cooperate with humans in a task requiring physical interaction and decision making is an encouraging step toward natural and intuitive human-robot cooperation. The present results are of course limited to a single one-dimensional task with binary choice, and further studies are needed to test possible generalization to more complex situations. Future work will also include the generalization to others tasks and extension to multiple degrees of freedom.

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