Modeling the Interaction Force During a Haptically-Coupled Cooperative Manipulation

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Abstract—One of the most challenging aspects of cooperative manipulation is coordination process between haptically-coupled subjects. The interaction force is believed to play a significant role in this process. In this paper, we propose a model for the interaction force and validate our model through a human study. The human study includes both bimanual and dyadic modes in three different scenarios, specifically designed to study the effect of coordination process in performance of the cooperation. We consider five different performance metrics to measure several aspects of the cooperation. The statistical analysis of these performance indexes proves that, while our model can explain the human behavior in different scenarios and different modes, the alternative models fail to do so.

I. INTRODUCTION

Cooperative object manipulation is an interesting research problem in haptic community. While human movements have been studied extensively and many theories and predictive models have been developed to describe certain regularities in human motions, modeling the interactions of haptically-coupled subjects is still a challenging problem. In order to understand the characteristics of a cooperative haptic interaction, researchers have studied different aspects of physical collaboration between humans in cooperative tasks.

In one line of research, the behavioral properties of cooperative tasks has been studied. For instance, Guiard [1] suggested that in bimanual tasks, while one arm performs the majority of the workload, the other arm is responsible for fine tuning and corrections. Reed et al. [2] observed arm specialization in a dyadic task where one person is contributing more to acceleration and the other person to deceleration. Mörtl et al. [3] studied the process of role assignment (leader/follower roles) during the physical cooperation. Van der Wel et al. [4] showed that in an object manipulation task, dyads amplify their applied forces to develop a haptic communication channel.

In another line of research, the performance of cooperative tasks have been the focus of the research. Noohi and Žefran [5] characterized a dyadic object manipulation task and proposed a set of measures that evaluate the performance of haptically-coupled subjects and cross-validated those metrics with the subjects’ self-assessments. Groten et al. [6] suggested that in a shared decision making situation, the haptic channel enhances the intention integration and results in a higher performance. Ganesh et al. [7] reported that haptically-coupled subjects demonstrate better motor performance than a single person in a virtual pursuit tracking task. Feth et al. [8] studied a joint-pursuit-tracking task and observed that the performance of a dyadic collaboration is higher than for single individuals.

Some other researchers studied the human intent during a cooperative task. For instance, Basdogan et al. [9] suggested that haptic clues convey rich information about the interaction in shared virtual environments. Based on Hidden Markov Models (HMMs), Medina et al. [10] proposed a prediction framework and introduced a risk-sensitive optimal controller [11] to estimate the human-intended trajectory. Bussy et al. [12] proposed motion primitives for cooperative transportation of heavy objects and introduced a velocity-based algorithm to generate a sequence of such proposed primitive motions. Dumora et al. [13] proposed a classifier to map the haptic measurements to the human intent. In a goal-directed object swinging task, Donner et al. [14] proposed a mapping for haptic information to the variations of energy that facilitates estimation of the human intent.

One of the most challenging aspects of cooperative manipulation is the interaction force between haptically-coupled subjects. Studying the properties of the exchanged forces is a very interesting problem. We will present the standard formulation of the problem in Sec. II and show that the system is an under-determined system of equations. We will discuss other researchers’ approaches to this problem and introduce few existing models for the interaction force. In Sec. IV, we will discuss our proposed treatment for the problem and introduce our model for the interaction force. To validate the proposed model, we will conduct a human study and apply the proposed model to the data that we collect during the human study. We will compare the performance of the proposed model with the existing models and show that our model performs significantly better in revealing the characteristics of the cooperation.

II. PROBLEM STATEMENT

In this work, we focus on dyadic object manipulation tasks and take the general case where both hands can apply both force and pure torque to the object. Let \( f_1 \) and \( f_2 \) refer to the forces that are applied to the manipulated object and \( F_{\text{sum}} = f_1 + f_2 \) be the resultant force that is associated with the task. Each applied force can be decomposed into the effective force (\( f_1^{e} \) and \( f_2^{e} \)) and the interaction force \( (F^{i}) \) as:

\[
\begin{align*}
    f_1 &= f_1^{e} + F^{i} \\
    f_2 &= f_2^{e} - F^{i}
\end{align*}
\]  

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The interaction force can be used to secure the grasp or to communicate with the other person [4], [15]. It can compress or stretch the object, but it does not influence the object’s equations of motion. As a result, all force components that lie in the null space of $F_{\text{sum}}$ (orthogonal to it) are part of interaction force. In other words, the effective forces need to be parallel with $F_{\text{sum}}$:

$$ \begin{cases} f^i_1 = \left( \frac{1}{2} + \delta \right) F_{\text{sum}} \\ f^i_2 = \left( \frac{1}{2} - \delta \right) F_{\text{sum}} \end{cases} $$

(2)

where $\delta$ indicates the contribution of each person in performing the task. Different values of $\delta$ represent different types of cooperation. For instance, $\delta = \frac{1}{2}$ is associated with the situation where $f^i_1$ provides the required force ($F_{\text{sum}}$) and $f^i_2$ provides the interaction force (e.g. securing the grasp). That is why $\delta$ is referred to by cooperativeness index, see [5]. Solving (1) and (2) for $F^i$ results in:

$$ F^i = \frac{1}{2}(f^i_1 - f^i_2) - \delta \cdot (f^i_1 + f^i_2) $$

(3)

According to (3), for any certain pair of the applied forces ($f^i_1$ and $f^i_2$), different values of $\delta$ (different effective forces) result in different interaction forces. That is, (1) and (2) construct an under-determined system of equations where any arbitrary value of $\delta$ introduces a valid decomposition. The only situation in which the system has a unique solution is when $F_{\text{sum}} = 0$. In such instances, $F^i = f^i_1 = -f^i_2$ and $f^i_1 = f^i_2 = 0$. In any other situation, in order to determine the interaction force one needs to introduce an additional constraint to the system (e.g. introducing specific values for $\delta$). Recall that, we take the general case where both hands can apply pure torque to the object and thus, no force-torque constraints exists in the system.

To uniquely determine the interaction force, researchers have considered different approaches and have introduced different constraints to the system. Some take the assumption that the cooperativeness index is constant during the task. For instance, taking $\delta = 0$ results in the well-known model of the internal force. This model is employed by many researchers, including [16]–[18]. We will discuss this model in more details in Sec. III-C. Another interesting selection of cooperativeness index is $|\delta| = \frac{1}{2}$, see [19]. This constraint suggests that a leader/follower role assignment exists between the subjects. Many researchers studied the exchange of the leader/follower roles between the subjects. For instance, Mörkl et al. [3] observed that dynamic role assignments resulted in a considerably larger interaction force. Evrard and Kheddar [20] suggested that a continuous homotopy switching happens between the leader and the follower roles during the collaboration (for each agent independently). However, they did not identify the homotopy function for dyadic tasks. Noohi and Žefran [5] took the assumption that the interaction force satisfies minimum-variation constraint and proposed a piece-wise linear model for the interaction force. We will show that the minimum-variation model is a special case of the model that we will propose in this work, see Sec. IV.

Groten et al. [21] studied the dominance distribution in a dyadic haptic collaboration. Inspired by optimality in many human movements, they took the assumption that the interaction force satisfies the minimum-energy constraint. We will discuss this model in more details in Sec. III-C.

III. BACKGROUND

Human movements have been studied extensively in the literature and many interesting theories have been established [16], [22]–[30]. In this section, we briefly review some of these theories to provide the required background for our discussions in the following sections.

A. Minimum Jerk Movement

It has been shown that many human movements, in particular single arm reaching movement, follow the minimum-jerk trajectory [22]. The minimum-jerk trajectory can be obtained by optimizing the jerk function along the movement path. That is:

$$ x^*(t) = \arg\min_{x(t)} \left\{ \frac{1}{2} \int_{t_1}^{t_f} \left\| \frac{d^3 x(t)}{dt^3} \right\|^2 dt \right\} $$

(4)

where $x(t)$ is the position trajectory, $t_1$ is the time that the movement is initiated and $t_f$ is time that it is finished. Using the calculus of variations, it has been shown [31] that the solution to (4) is in the form of a 5th order polynomial. That is:

$$ x^*(t) = \sum_{k=0}^{5} a_k t^k $$

(5)

To be able to determine the $a_k$ coefficients, the boundary conditions should be taken into consideration. If we assume that the motion starts and ends at rest (zero boundary conditions), the minimum jerk trajectory would be:

$$ x^*(\tau) = x_i + L(6\tau^5 - 15\tau^4 + 10\tau^3) $$

(6)

where $\tau = (t - t_i)/(t_f - t_i)$ is the normalized time and $L = \|x_i - x_f\|$ is the traveled distance. Here, $x_i = x(t_i)$ and $x_f = x(t_f)$ are the initial and the final positions of the movement, respectively.

B. Movement Inside a Force Field

Many studies show that humans can adapt to the external force field and his/her motion trajectory will return to its original trajectory (in the absence of the field) after enough learning trials [27]–[29]. In case of the minimum-jerk movement, this theory suggests that the motion trajectory return to the well-known bell-shape velocity profile and it is robust to the external disturbances. Let us consider a dyadic object manipulation where each person introduces a disturbance force to the other person’s hand. According to the above theory, after the familiarization phase both persons learn to cooperatively move the object on a minimum-jerk trajectory. In fact, we have recently shown that the motion trajectory of the object during a cooperative object manipulation task is strongly correlated with the minimum jerk trajectory [30].
C. Interaction Force Models

Researchers have taken different approaches in modeling the interaction force. Here we introduce two of those models that have received the most attention in the literature. The first model is inspired by the mechanical characteristics of the objects when several forces are exerted on them. The second model is inspired by the hypothesis that humans are energy efficient when performing physical activities.

Internal Force:
In this model, the assumption is that the effective forces would not contribute to the mechanical strain of the object (also known as engineering strain). In case of a dyadic object manipulation, this assumption requires the effective forces to be equal, i.e. \( f_1^* = f_2^* \). Applying this equation in (1) results in:

\[
\begin{align*}
F^i &= \frac{1}{2}(f_1 - f_2) \\
F^i_{\text{sum}} &= \frac{1}{2}(f_1 + f_2)
\end{align*}
\]

where \( \delta(t) = 0 \). Eq. (7) suggests that the interaction force is equal to the mechanical internal force that appears during a cooperative manipulation [32]. Since this model takes the object’s mechanical characteristics into the consideration, many researchers have employed it as an explanation for the interaction force; see [16] as an example.

Minimum Energy:
Here, the assumption is that humans do not apply unnecessary interaction forces to the object; they apply interaction forces only when the task demands it (such as securing grasp stability). For a certain pair of the applied forces \((f_1, f_2)\), this assumption can be formulated as:

\[
\delta(t) = \text{argmin}_\delta \left( ||F^i|| \right)
\]

where

\[
F^i = \frac{1}{2}(f_1 - f_2) - \delta F_{\text{sum}}
\]

An example of employing this model is [21], where the dominance distribution in a dyadic haptic collaboration is investigated.

IV. PROPOSED MODEL FOR THE INTERACTION FORCE
To model the internal force, we observe that while it would not affect the object’s motion profile it can compress or stretch the object. Therefore, if we employ a model for the object deformation, it would introduce the associated internal force. Considering different types of elastic deformation (compress, stretch, sheer, twist, etc), the following equation describes the most general form of linear relation between the internal force and the deformation strain:

\[
F^i = \sum_{k=0}^{N} b_k \frac{d^k \epsilon}{dt^k}
\]

where \( \epsilon(t) = (l(t) - L)/L \), \( L \) is the original length of the object and \( l(t) \) is length of the deformed object. The order of the model is determined by the value of \( N \) (where \( 0 \leq N \leq \infty \)). In the case of a linear spring \((N = 0)\), we obtain the simplified version of (9) as \( F^i = \beta_0 \epsilon \). Considering this deformation model for a dyadic object manipulation task, the deformed object length can be obtained as:

\[
l(t) = x_2^*(t) - x_1^*(t)
\]

where \( x_1^*(t) \) and \( x_2^*(t) \) are the movement trajectories of the subjects. As discussed in Sec. III-B, we assume that both humans would perform a minimum-jerk trajectory as a result of a learning process. In other words, both \( x_1^*(t) \) and \( x_2^*(t) \) are minimum-jerk trajectories and are represented by 5th order polynomials; see (5). Plugging (5) into (10) and the result into (9) would reveal that:

\[
F^i(t) = \sum_{k=0}^{5} c_k t^k
\]

In order to determine the coefficients in (11), the boundary conditions can be used. The boundary conditions correspond to the times \( t_i \) where \( F_{\text{sum}}(t_i) = 0 \). At those times, \( f_1(t_i) = f_2(t_i) = 0 \) and \( f_1(t_i) = -f_2(t_i) \). Therefore, \( F^i(t_i) = f_1(t_i) \), see (1). As discussed in Sec. III-B, \( F_{\text{sum}} \) is associated with a minimum-jerk trajectory [30] and therefore, it has exactly one zero crossing point, namely \( t_m \). Taking \( t_i \) and \( t_f \) as the start time and the end time of the motion, \( F_{\text{sum}}(t_i) = 0 \) for \( t_i \leq t_i, t_f = t_m \) and \( t_f \geq t_f \). This results in the following set of boundary conditions:

\[
F^i(t_i) = f_1(t_i) \\
F^i(t_m) = f_1(t_m) \\
F^i(t_f) = f_1(t_f)
\]

The smoothness of the applied forces imposes additional constraints on the internal force: the derivatives of the applied forces should also be continuous. Fig. 1 shows the results of applying the proposed model to the signals obtained in a bimanual object manipulation. As it appears in this figure, the internal force (red dash-dotted signal) varies smoothly between the initial and final grasp forces. Also, the model suggests an effective cooperation between the effective forces (\( \delta \approx 0 \)), as expected in bimanual mode.

It is worth mentioning that if the smoothness constraint is relaxed, some variations of the proposed model can be obtained. For instance, a piece-wise linear function that satisfies the boundary conditions in (12) introduces a model...
for the interaction force. This model has been employed in [5] to quantify the human perception of the cooperativeness of a collaborative task.

To validate our model and evaluate its performance in comparison with the existing models in the literature, we design a human study. In the following section we describe the details of the method we use for this study and discuss the results in the following section.

V. METHOD

To study bimanual reaching movement, the subjects are asked to grasp an object with both hands and move it horizontally. Then the subjects are grouped into pairs and perform dyadic reaching movements, cooperatively. In both cases, the grasps are power-grasp and the subjects can apply independent forces and torques to the object.

A. Apparatus

We choose a pot as the object to be carried bimanually. To measure the forces applied by the subjects, we use two SI-65-5 ATI Gamma force sensors [33]. The force sensors are placed in between each handle and the pot. The forces are sampled by two PCI-6034E NI DAQ boards [34] at the frequency of 1 KHz. The acquired data is then transformed to the earth reference frame. This requires the orientation of the pot to be measured. We use a 9DOF-Sensor-Stick SparkFun IMU to measure the pot’s orientation and acceleration [35]. The sampling frequency for the IMU is set to 100 Hz. The IMU is interfaced with the computer through an Arduino Mega microcontroller board [36]. All data collection is managed through a Matlab GUI that we have developed. Fig. 2 shows the experimental setup and its components.

B. Procedure

In this work, we study both bimanual and dyadic reaching movements in three different cooperation scenarios. In bimanual mode, each subject performs a bimanual reaching movement, alone. We will refer to this case as single-person bimanual (SPB) scenario. The next two scenarios are in dyadic mode. In the first scenario, a leader and a follower role is assigned to each pair. The leader is initiating all the subtasks, while the follower is told to follow his/her lead. This case is referred to as the leader-follower (L/F) scenario.

To study the effect of the lag between the leader and the follower in L/F scenario (at the beginning of the movement), we introduce a synchronized-cooperation scenario. In this scenario, an audible marker (beep) is played at fixed points in time by the software and the subjects are told to execute each subtask right after hearing the beep (no roles are assigned to the subjects). Therefore, the start time of the reaching movement is known for both subjects and the lag between the subjects at the beginning should disappear. This case is referred to as the synchronized (Sync) scenario.

Each trial of the experiment consists of three subtasks; lifting the pot from the table at the start point (point A), moving the pot horizontally towards the destination point (point B) and putting the pot down on the table at the end point. Studies show that gravity plays a significant role in single-arm vertical reaching movements [37], [38]. Therefore, in this study we focus on the horizontal movements and discard the first and last subtasks in each trial. We will consider these vertical movements in our future work.

The configurations of the start points and the end points are designed in such a way that we have two types of horizontal motions. In type 1 motions, the direction of the motion is perpendicular to the line connecting the handles. Therefore, the grasp force has small components in the motion direction. In type 2 motions, the direction of the motion is parallel with the line connecting the handles and, grasp force has dominant components in this direction, see Fig. 3. Also, the distances between the start points and the end points are selected such that both short-range and long-range motions are included. In the short-range motions, the horizontal distance between the start point and the end point is 28 cm and, in the long-range motions it is 83 cm.

Each subject is given as many familiarization trials as they need. Then, he/she performs three trials in SPB scenario, including a short-range type 1 motion, a short-range type 2 motion and a long-range type 2 motion. The long-range type 1 motion is excluded, because it is not within the range of human-arm reachable space. In dyadic mode, each pair performs three trials in Sync scenario following by two trials in L/F scenario. In the Sync scenario, the short-range type 2 motion is excluded. In the L/F scenario, each pair performs a long-range type 1 motion. Then the subjects switch the leading role and repeat the task. In all of the trials, no repeated measurements are collected.
C. Evaluation

To eliminate the high frequency noise, a low pass FIR smoothing filter is applied to the signals. It is a 7th-degree polynomial Savitzky-Golay filter [39] with the frame size of 201 and the cutoff frequency of 12.5 Hz. To be able to quantitatively compare different models of the interaction force, we employ five performance metrics as follows. A complete list of related indexes and their interpretations (according to the associated human assessment) has been presented in [5].

Cooperation Index:
The Cooperation index is defined as:

\[
I_c = 1 - \frac{I_d}{\max(I_d)}
\] (14)

The index measures the average value of \( \delta \) during the task, and is related to the average internal force that is present. Since the index is not bounded, we use the maximum value among the calculated samples and scale them to the range of zero and one. That is:

\[
I_c = 1 - \frac{I_d}{\max(I_d)}
\] (14)

We will refer to this normalized index \( I_c \) as the Cooperation index, hereafter. The higher values of the Cooperation index indicate a better cooperation among the subjects (smaller \( \delta \)).

Comfort Index:
We define the Comfort index based on the Difficulty index. The Difficulty index is defined as:

\[
I_d = \frac{1}{t_f - t_i} \int_{t_i}^{t_f} M_d(t) \, dt
\] (15)

where \( M_d(t) = \| \delta(t) \| \). The index evaluates the difficulty of the task by measuring the degree of required mental demand. The higher values of the index indicate more difficult task. The Comfort index is defined by normalizing the Difficulty index. That is:

\[
I_o = 1 - \frac{I_d}{\max(I_d)}
\] (16)

The higher values of the Comfort index indicate simpler tasks with less mental demands (\( I_o = 1 \) when \( \delta(t) = \text{const.} \)).

Efficiency Index:
The Efficiency index is defined as:

\[
I_e = \frac{1}{t_f - t_i} \int_{t_i}^{t_f} M_e(t) \, dt
\] (17)

where

\[
M_e(t) = \frac{\| F_{\text{sum}}(t) \|}{\| f_1(t) \| + \| f_2(t) \|}
\]

This measure represents the extent of disagreement of the dyad members in performing the task. The higher values of the index indicate less wasted efforts. The index is suitably bounded between zero and one (\( 0 \leq I_e \leq 1 \)), see [5].

Similarity Index:
The Similarity index is defined as:

\[
I_s = \frac{1}{t_f - t_i} \int_{t_i}^{t_f} M_s(t) \, dt
\] (18)

where

\[
M_s(t) = 1 - \frac{\| f_1(t) \| - \| f_2(t) \|}{\| F_{\text{sum}}(t) \|}
\]

This index measures the similarity of the effective forces (symmetry with respect to the task). Higher values of the index indicates more symmetry between the effective forces. The index is suitably bounded between zero and one [5].

Fairness Index:
The Fairness index is defined as:

\[
I_f = 1 - \frac{N_1 - N_2}{N_{\text{sum}}}
\] (19)

where

\[
N_1 = \int_{t_i}^{t_f} \| f_1(t) \| \, dt
\]

\[
N_2 = \int_{t_i}^{t_f} \| f_2(t) \| \, dt
\]

\[
N_{\text{sum}} = \int_{t_i}^{t_f} \| F_{\text{sum}}(t) \| \, dt
\]

It measures the inequality between the effective efforts in terms of the signal-energy. The higher values of the index indicate smaller differences between the contributions of the subjects (in terms of signal-energy of the forces). The index is suitably bounded between zero and one (\( 0 \leq I_f \leq 1 \)) [5].

VI. RESULTS

A human study was conducted with 22 adult subjects, consisting of 12 men and 10 women between 19 and 35 years of age. Discarding the corrupted measurements, we collected 58 trials in SPB scenario, 31 trials in Sync scenario and 21 trials in L/F scenario (a total of 52 trials in dyadic mode). Employing the model explained in Sec. III-C, the internal forces, \( F^e(t) \), were calculated for all trials.

To evaluate the performance characteristics of the proposed model, we use the indexes introduced in Sec. V-C. The values of the indexes are highly associated with the value of the internal force and the effective forces. Therefore, different models demonstrate different performance for the same pair of signals \( (f_1, f_2) \). This helps us to evaluate different models and compare them using the results of the performance evaluation.

We applied our proposed polynomial model (Poly), the internal force model (IntF) and the minimum energy model (MinE) to the collected signals for all trials \( (f_1, f_2) \) and obtained all internal forces and effective forces for each model. To calculate the performance indexes, we applied (13)-(19) to these internal and effective forces. Therefore, we obtained 110 samples for each index per model (total \( 110 \times 5 \times 3 = 1650 \) samples). We looked into the effect of two factors in the data: cooperation and coordination.

To study the effect of the cooperation-types on the performance of the task, we grouped samples for different modes (bimanual and dyadic) together and ran an anova test on
these groups (for each index per model). That is, we ran a total of 15 tests (five index per model for three models). To investigate the effect of the coordination on the performance of the task, we grouped samples for different scenarios (SPB, Sync and L/F) together and ran an anova test on these groups (for each index per model, resulting another 15 tests). The significance level was $\alpha = 5\%$ in all tests.

Fig. 4 depicts the tests results regarding the effect of cooperation-type on the performance. Panels (a), (b) and (c) in this figure show these results for the Poly model, IntF model and MinE model, respectively. In all charts, the green patches are associated with bimanual mode and the cyan patches present stats of the dyadic mode. The depicted stats are the confidence intervals for the performance indexes. Recall that since all indexes are bounded between zero and one, and the higher index values are associated with higher performance, the charts axes are all between zero to one, with zero at the center of the chart.

As illustrated in Fig. 4a, the proposed model suggests that the performance of the single person bimanual manipulation is significantly higher than the dyadic manipulation for almost all indexes ($F(1,108) > 8, p < 0.005$ for four tests). The exception is the Fairness index ($I_f$) where the performance is not significantly different ($F(1,108) = 2.3, p = 0.13$). As shown in Fig. 4b, no discrepancy is observable when the IntF model is employed. That is due to the fact that $\delta = 0$ for all trials. In other words, IntF model suggests that all trails were performed with a perfect cooperation and a perfect performance. Finally as depicted in Fig. 4c, the MinE model suggests that no significant difference exists between the single person bimanual manipulation and dyadic manipulation, regarding the Cooperation ($I_c$), Similarity ($I_s$) and Comfort ($I_o$) indexes ($p > 0.6$ for all). It suggests that bimanual mode performed significantly better than the dyadic model ($F(1,108) = 9.3, p = 0.003$), while it performed significantly worst in the Efficiency index ($F(1,108) = 4.4, p = 0.038$).

Ignoring $I_f$, these results show that the proposed model can effectively detect the performance superiority of the bimanual cooperation. On the contrary, other models are unable to discover the performance difference between cooperation types. Moreover, the MinE model suggests the hypothesis that the efficiency of the single-person bimanual manipulation is significantly lower than the dyadic manipulation. This hypothesis is not only counter-intuitive, but also in contradiction with the human assessments reported in [5].

To better understand the Fairness index ($I_f$), let us first consider the collected signals in type 1 motions for bimanual tasks. Here, the interaction forces are negligible and applied forces are good approximations of the effective forces. The data shows that in many of the trials, the forces are proportional (e.g. $\delta = 0.1$), which leads to different signal-energies for hands and adversely affects on $I_f$ (e.g. $I_f = 0.8$ for $\delta = 0.1$). In other words, we do not observe similar contributions ($I_f \approx 1$) for the hands in bimanual type 1 motions. This observation explains the similarity of the $I_f$ when Poly model is employed. On the contrary, MinE model suggests that in bimanual mode, hands perform less different than dyadic mode. We speculate that it is a result of MinE model and Fairness index being both defined based on the concept of the energy of the signals.

Fig. 5 depicts the tests results regarding the effect of coordination on the performance. Panels (a) and (b) in this figure show these results for the Poly model and MinE model, respectively. We excluded the chart for IntF model, because its results were constant in all tests. In both charts, the green, blue and red patches are associated with SPB, Sync and L/F scenarios, respectively. According to the test results, the proposed model suggests significantly (for $I_c$, $I_s$), strongly ($I_o$) or weakly ($I_o$) performance differences between the scenarios, but no significant difference on $I_f$. On the contrary, MinE model only suggest a significant difference between SPB and L/F for $I_f$ ($p = 0.001$). As illustrated in Fig. 5a, the Poly model clearly uncovers the performance improvement trend, resulted by the coordination mechanism. It suggests that the average performance in the synchronized scenario (Sync) is higher than dyadic leader-follower scenario (L/F), but not as high as a single person in SPB scenario.

To better visualize the trends that exists between different scenarios, Fig. 6 presents three spider charts, comparing different pairs of scenarios with each other. Note that each
If of SPB scenario over both Sync and L/F. It also suggests a
effectively identifies the significant performance superiority
from Fig. 5a. Similar to previous figure, The green, blue
of scenarios and therefore, the patches are slightly different
proposed model. The green, blue and red charts represent the stats
Fig. 6: Radar charts comparing different scenarios, based on the
problem.

In this paper we proposed a model for the interaction force
between haptically-coupled subjects. First, we presented the
standard formulation of the problem and showed that it
results in an under-determined system of equation. Then, we
proposed that by integrating the knowledge of the task and
the mechanical properties of the object, one can determine
the interaction force. We showed that in case of dyadic
reaching movements, the interaction forces can be modeled
by a polynomial function. To validate our model and evaluate
its performance, comparing with the existing models in the
literature, we designed a human study.

The human study comprised two modes, single-person
bimanual and dyadic, in three scenarios. The scenarios were
designed to investigate the correlation between the perfor-
ance improvement and the coordination process. Human
assessments had shown that better coordination results higher
performance [5]. We considered five performance metrics to
explore different aspects of cooperation, including: co-
operativeness, similarity, fairness, efficiency and difficulty.
We showed that when the proposed model is employed, a
significantly higher performance is observable in bimanual
mode and also an improvement trend is associated with the
coordination process. We also discussed that while our model
can effectively uncover human behavior, the alternative mod-
els fail to do so.

The focus of our work has been on linear motions with
the minimum jerk trajectory profile. Studying other types of
human movements and validating this model in other tasks
would be an interesting extension to this work. Furthermore,
by implementing this model on a robot, one can verify the
applicability of this approach in a human-robot interaction
problem.

VII. Conclusion

The focus of our work has been on linear motions with
the minimum jerk trajectory profile. Studying other types of
human movements and validating this model in other tasks
would be an interesting extension to this work. Furthermore,
by implementing this model on a robot, one can verify the
applicability of this approach in a human-robot interaction
problem.

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