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Cooperation or collaboration? On a human-inspired impedance strategy in a human–robot co-manipulation task

Lorenzo Vianello[4], Waldez Gomes[1,3], Pauline Maurice[1], Alexis Aubry[2], Serena Ivaldi[1]

Abstract— **Robotic manipulators have the capability to engage in physical interaction with human operators, sharing not only the same workspace but also offering physical assistance to alleviate the human physical workload. In this study, we explore whether a robot should act as a collaborator or a cooperator in a co-manipulation task with a human partner, and investigate different collaboration strategies. In a previous study, we addressed the same question for a human–human dyad and found that collaboration is preferable to make fewer errors at the expense of increased arm stiffness for the humans. In our current investigation, a human physically interacts with a Franka robot in various co-manipulation conditions. In the cooperation conditions, the robot is either a leader or a follower, exhibiting fixed impedance strategies. In the collaborative conditions, the robot exhibits either reciprocal or mirrored adaptive impedance strategies that vary according to an online EMG-based function of the human arm stiffness. Our findings indicate that, for co-manipulation tasks, a robot collaborator is preferable to a robot cooperator (leader or follower), similarly to human dyads. However, unlike the behavior observed within human dyads, the reciprocal strategy for impedance adjustment appears to be the most effective for human–robot collaboration.**

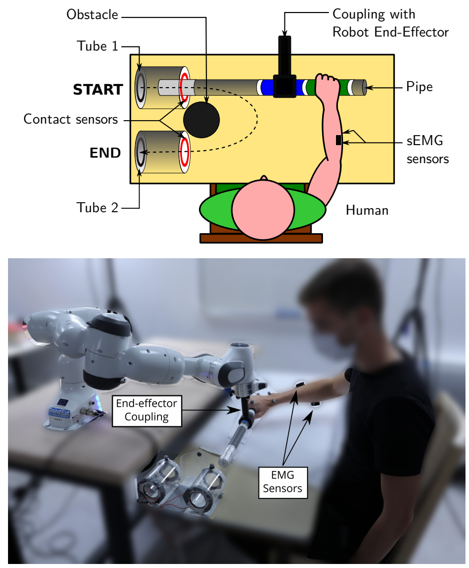

Fig. 1. Human–robot co-manipulation study. *Top:* Top-down view of the experiment set-up. The dashed line approximates the pipe trajectory. *Bottom:* A participant performing the task with the Franka Emika robot.

I. Introduction

Robotics solutions have the potential to improve the working conditions of human operators in industry [1]. Due to enhanced sensing and control capabilities, robotic manipulators can engage in physical interaction with human operators, sharing the same workspace and offering physical assistance to alleviate the human physical workload [2]. However, the acceptance of sharing workspace with collaborative manipulator robots may not be straightforward for human workers [3], [4]: in particular, it could be easier to interact with a robot that has a fixed role in the interaction, rather than with a robot with complex and less predictable behavior. This preference may not necessarily relate to better performance in task execution. This observation led to an investigation into the type of behavior (cooperation or collaboration) a robot should adopt while executing a co-manipulation task with a human, and whether this behavior has any relation to how two humans physically interact to solve the same task.

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[1]Université de Lorraine, CNRS, Inria, LORIA, F-54000 Nancy, France. pauline.maurice@loria.fr

[2]Université de Lorraine, CNRS, CRAN, F-54000 Nancy, France.

[3]Université Paris-Saclay, CIAMS, 91405, Orsay, France.

[4]Legs and Walking Lab of Shirley Ryan AbilityLab, Chicago, IL, USA.

In this work, we distinguish between cooperation and collaboration as defined by Jarrassé et al. [5]. If before the co-manipulation, the agents have been assigned, or have agreed upon, different roles (asymmetric responsibilities) to execute the task, then the interaction is classified as a *cooperation*. A common example of cooperation occurs when the agents assume leader–follower roles, wherein one of the two agents takes on a greater decision-making role, while the second simply adapts to the gestures of the first. In contrast, during a *collaboration*, both agents form a "spontaneous" coalition to accomplish the task [6]: their "activity is synchronized and coordinated in order to build and maintain a shared conception of a problem" [7]. That is, in collaboration, the agents may deliberate and negotiate their roles in executing the task to accomplish the dyad's common goal.

In co-manipulation, roles can be defined by stiffness profiles of the arm endpoint. For example, in the leader–follower roles distribution, the leader adopts a high stiffness profile, while the follower assumes a low stiffness [8]. It is frequent to find this configuration in rehabilitation robotics, for example, when robotic arms (leaders) guide the patients' arms (followers) along desired trajectories [9]. Between the two extreme roles and corresponding stiffness values, there is a continuous range of stiffness values that can be exploited to obtain more stiff or more compliant behaviors: for this reason, previous work investigated how to adapt the arm stiffness (and the corresponding impedance) in this range to implement adaptive compliant behaviors in robotic arms [10]. Other research on tele-impedance [11], shared control [12] and co-manipulation [13], [14] confirms that an adaptive stiffness behavior determines the performance of a human–robot collaboration.

In our previous work, we studied human–human interaction and observed a better performance (i.e., fewer task errors) for human dyads when there was no clear role allocation (i.e., when they were collaborating), at the expense of a higher effort [15]. Indeed, during collaboration, both human partners had similarly high levels of arm muscle co-contraction and, therefore, higher levels of arm stiffness, as if they were both leaders. This previous study showed that collaborating humans mirror their stiffness: could this be a legitimate collaborative strategy also for a robotic collaborator? In this paper, we therefore focus on a human–robot co-manipulation task where an object has to be carefully extracted from a tube and inserted into another one. This task requires precision, and we expect the stiffness of each agent to be critical to reject disturbances that may lead to task failure. In this context, we identify the following research questions: (1) Is it more efficient for the human–robot dyad to cooperate or to collaborate? (2) When collaborating, should the robot have a stiffness behavior proportional (imitation) or inverse (reciprocal) to the user? (3) Do the findings from human–human dyads transfer to human–robot dyads?

To answer these questions, we conducted a study on 15 participants physically interacting with a robot in the same experimental scenario of our prior human–human study (Fig. 1). We investigated the performance, human arm stiffness, and human preference when the dyad was cooperating and collaborating, across four conditions. In cooperative conditions, the robot was either leader or follower, and vice-versa for the human. In the collaborative conditions, we implemented two possible collaborative impedance strategies: the first, inspired by the previous study, mirrored the human stiffness, while the second, inspired by [16], reciprocated the human stiffness.

In this paper, we briefly overview our previous human–human study, and report on the methodology and results of the human–robot study, discussing the implications of the results for future collaborative robotics technologies.

II. Related Work

Human–robot cooperation is often formalized by fixed roles determined by coordination between the agents. The leader–follower role allocation approach, where the human is always the leader of the task, is likely the most traditional coordination strategy in physical Human–Robot Interaction (pHRI) [17]. In this case, the robot may be controlled to guarantee only certain aspects of the task execution, such as rejecting disturbances or sustaining forces and positions in different axes from the ones controlled by the human [18]. Ficuciello *et al.* use a more sophisticated strategy that explores the null-space of a redundant robot to decouple the apparent inertia at the robot end-effector, reportedly improving the intuitiveness of the task for the leader [19]. Even though the leader–follower approach meets great success in some applications such as robotic surgery [20], [21], and telemanipulation, there are instances in which adaptive or continuous roles could be preferred [22]. Cherubini *et al.* alternate the leader and follower roles of a robot in a pHRI application for industry according to visual and haptic cues by the human co-worker [14]. Khoramshahi and Billard propose a method to automatically detect when a human co-worker is physically trying to guide a robot that is executing an autonomous task [23]. After the intent detection, the robot switches into follower mode and only returns to leader mode when the human stops correcting the robot. Peternel *et al.* adapt the behavior of a collaborative robot from follower to leader based on the detected human physical fatigue level in a collaborative sawing task [24]. Agravante *et al.* interpolate between a humanoid robot's behavior from a total leader to a total follower (each behavior corresponds to a different walking pattern generator to the humanoid robot) [25]. During the leader behavior, the robot controller minimizes the errors for the desired trajectory (high impedance), whereas, for the follower behavior, it minimizes the forces applied to the human operator (low impedance).

Therefore, in the literature, it is often the case that either the roles are fixed (cooperation) or they are adapted according to a strategy (collaboration). However, to the best of our knowledge, little is known about the comparative effect of both approaches on a same task. In this work, we thus compare cooperation vs. collaboration in the same co-manipulation task, in order to inform about which one is preferable for a successful and comfortable interaction. We bear in mind the outcome of a previous study that investigated human–human cooperative and collaborative behavior in the same task. Our rationale is that if collaboration is preferable for a joint task realized by a human dyad, there is a possibility that it would be preferable also for human–robot interaction. Yet, a robot cannot fully reproduce complex human behavior, so it is possible that human–human results do not transfer to human–robot situation. So we target the question of which impedance behavior the robot should exhibit to collaborate proficiently and, whether this behavior should imitate and adapt online to the one of a human partner.

For this reason, in this work we investigated the use of *tele-impedance*, namely the transfer of impedance from human signals to robot control [26]. Peternel *et al.* proposed two control strategies (robot reciprocal and robot mirrored) based on the concept of tele-impedance [16], [24]. During Reciprocal tele-impedance the robot and the human operator execute two behaviors that are reciprocal in terms of phase of operation (e.g. sawing task). On the other side, during mirrored tele-impedance, both agents produce the same behavior in a certain phase of the task (e.g. valve turning). Their work led us to question whether this kind of adaptation could in any way be traced back to the collaboration observed during the human–human experiment.

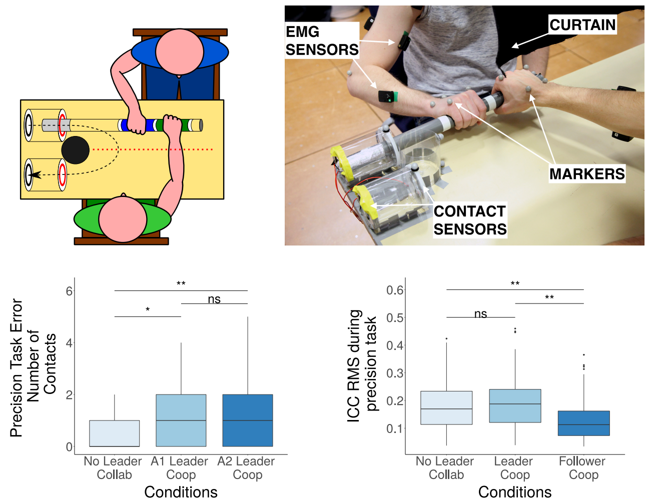

Fig. 2. Human–human co-manipulation study [15]. *Top left:* Top-down view of the experiment set-up. The black dashed line approximates the pipe trajectory. The red circles are contact sensors used to detect any contact between the pipe and the tubes' front walls. The red dashed line represents a curtain placed between both agents to prevent visual eye-to-eye communication. *Top right:* Experimental set-up. *Bottom left:* Number of contact between the pipe and the tubes' walls (errors), for each condition. *Bottom right:* Root Mean Square value of the index of co-contraction (*icc*) during the extraction and insertion phases, for each condition.

III. Background: Human–Human Dyad Experiment

We previously conducted an experiment in which a task was executed by two physically interacting human partners, i.e. a human–human dyad (Fig. 2) [15]. The participants executed the task under two main conditions: *Cooperative*: Agent 1 is assigned the leadership while Agent 2 is the follower and vice-versa; *Collaborative*: there is no pre-assigned leadership (and no verbal or visual communication). During the task execution, we measured the participant's muscle activation, as well as their accuracy at executing the task for each trial. The human–human dyads made fewer errors without pre-assigned roles than when there was a leader. In addition, we observed that when there was no pre-assigned leader, the agents had a muscle co-contraction level as high as when they were leaders of the task. Since muscle co-contraction is associated with arm stiffness, we hypothesize here that robots similarly modulating their impedance could emulate the aforementioned human motor behavior.

IV. Methods

To investigate how human–human dyads' motor behavior transfers to human–robot dyads, we conducted an experiment in which 15 human participants performed a co-manipulation task with a robot under different conditions. Namely, four profiles were defined for the robot end-effector impedance, to implement *cooperation* and *collaboration* conditions. The experiment is detailed hereafter.

A. Experimental set-up

1) Participants: Fifteen healthy adults took part in the experiment (5 females and 10 males, aged 24–55). All participants performed the task with their right dominant hand. Participants were naive to the purpose of the study, and none reported any chronic motor disease or health condition that could influence the results. Participants signed an informed consent form before starting the experiment. The study was approved by INRIA's ethical committee COERLE and was conducted in accordance with the Declaration of Helsinki.

2) Task description: The task consisted in co-manipulating an object ($0.2\,kg$ pipe of diameter $3\,cm$ and length $50\,cm$) with a collaborative robot, in order to bring it from a start to an end point (Fig. 1). The task was divided into 3 phases. In phase 1 the pipe is within a tube (tube 1, close to the robot) and is extracted from it (hole diameter: $4.5\,cm$). In phase 2, the pipe is moved in free space in a horizontal plane, from tube 1 to tube 2, around a cylindrical obstacle. In phase 3, the pipe is inserted in a second tube (tube 2, close to the human). The return motion (from tube 2 to tube 1) is not part of the task. Participants were instructed to avoid contacts between the pipe and the tube's front wall during extraction and insertion phases. Such contacts were recorded, and counted as task errors. Performing the task once took between 15 and $25\,s$ on average, though there was no time instruction or limit. Participants were seated on a chair facing the robot and were instructed to avoid moving their backs during the task. They held the pipe with their right hand, on the designated handle, while the other handle was attached to the robot end-effector with a dedicated 3D-printed part.

3) Experimental design: Each participant performed the task in 4 different conditions, corresponding to different impedance behaviors of the robot (detailed in section IV-B):

- *Condition 1 – Robot Follower and Human Leader (RF):* Participants were instructed to lead the movement, while the robot is compliant with the human movement;
- *Condition 2 – Robot Leader and Human Follower (RL):* The robot lead the movement, while participants were instructed to be compliant.
- *Condition 3 – Robot Collaborator with Reciprocal Stiffness (RR):* Participants were not given any fixed role and were instructed to simply collaborate with the robot, which modulated its end-effector stiffness inversely to the human end-point stiffness.
- *Condition 4 – Robot Collaborator with Mirrored Stiffness (RM):* Participants were not given any fixed role and were instructed to simply collaborate with the robot, which modulated its end-effector stiffness proportionally to the human end-point stiffness.

According to the definition by Jarrassé *et al.* [22], conditions 1 (RF) and 2 (RL) correspond to a *cooperation* situation where the role of each agent (leader/follower) is pre-assigned, whereas conditions 3 (RR) and 4 (RM) correspond to a *collaboration* situation where agents have symmetric responsibilities.

Each participant performed 15 trials for each condition in a block manner, for a total of 60 trials. Participants were given a $30\,s$ break between each trial, and a $5\,min$ break between each condition. Condition 1 (*robot follower*) was always performed first, as it was used to estimate scaling parameters needed for the implementation of the robot control in the two *collaboration* conditions (see Section IV-B.2). The order of the three remaining conditions was randomized. Before starting the actual experiment, participants performed a few practice trials in *robot follower* condition to familiarize themselves with the task and the robot.

4) Instrumentation and performance metrics:

a) Pipe–tube contact: The main objective of the task was to extract/insert the pipe from/into the tubes without touching their front walls. Those walls were therefore equipped with custom contact sensors to detect contacts with the pipe. The contacts were recorded at $1\,kHz$ using a Raspberry Pi. Due to the reaction time of the human, contacts that were separated by less than $0.5\,s$ were counted as a single contact.

b) Human end-point stiffness: Participants were equipped with 2 Delsys Trigno wireless sEMG sensors on antagonist muscles of their right forearm (FCU: Flexor Carpi Ulnaris and ECU: Extensor Carpi Ulnaris) to record muscle activity. EMG signals were recorded at $2\,kHz$, and filtered online using a $100\,ms$ RMS window followed by a lowpass 3rd order Butterworth filter with a $10\,Hz$ cutoff frequency. The filtered signal u^k (for muscle k) was then normalized by its maximum voluntary contraction value u^k_{MVC} measured before starting the experiment. Finally, a co-contraction index icc was computed based on the normalized EMG value of both muscles [27], [28], that served to estimate the human end-point stiffness:

$$icc(t) = min\left(\frac{u^{FCU}(t)}{u^{FCU}_{MVC}}, \frac{u^{ECU}(t)}{u^{ECU}_{MVC}}\right). \tag{1}$$

c) Questionnaires: At the end of each experimental condition, participants were asked to fill out a questionnaire including 2 questions: *Q1: From 1 to 10, how easy was it to do the task with the robot (1=not at all easy, 10=very easy)?, Q2: From 1 to 10, how much did the robot prevent you from doing the task the way you wanted (1=much prevented, 10=not prevented at all)?* At the end of the entire experiment, participants also reported orally their preferred condition.

B. Robot control and collaborative impedance strategies

The experiment was performed with a Franka Emika robot. The robot was controlled with an end-effector Cartesian impedance scheme, that allowed to easily implement different compliance behaviors. We considered the robot equation of motion: $\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau} - \boldsymbol{J}^\top \boldsymbol{F}_{ext}$ with $\boldsymbol{M} \in \mathbb{R}^{n\times n}$ the inertia matrix, $\boldsymbol{C} \in \mathbb{R}^{n\times n}$ the matrix of Coriolis and centrifugal effects, $\boldsymbol{g}(\boldsymbol{q}) \in \mathbb{R}^n$ the vector of gravity forces, $\boldsymbol{J} \in \mathbb{R}^{6\times n}$ the end-effector Jacobian, $\boldsymbol{\tau} \in \mathbb{R}^n$ the joint torque vector, and the interaction wrench at the end-effector is $\boldsymbol{F}_{ext} \in \mathbb{R}^6$. Using feedback linearization, $\boldsymbol{\tau}$ can be computed to achieve a desired mechanical impedance at the end-effector, such that:

$$\boldsymbol{F}_{ext} = \boldsymbol{K}(\boldsymbol{x_{ee}} - \boldsymbol{x_d}) + \boldsymbol{D}(\dot{\boldsymbol{x}}_{\boldsymbol{ee}} - \dot{\boldsymbol{x}}_{\boldsymbol{d}}) \tag{2}$$

where $\boldsymbol{K} \in \mathbb{R}^{6\times 6}$ and $\boldsymbol{D} \in \mathbb{R}^{6\times 6}$ are the desired stiffness and damping matrices in Cartesian space, and $\boldsymbol{x}_{ee}$ and $\boldsymbol{x}_d$ are respectively the actual and desired end-effector poses. The four different robot behaviors described in section IV-A.3 were implemented by changing the values and profiles of the $\boldsymbol{K}$ and $\boldsymbol{D}$ matrices, as explained hereafter. Only the translational stiffness and damping were modified across conditions, whereas the rotational part remained identical.

1) Cooperation conditions: The two cooperation conditions (RF: *robot follower*, RL: *robot leader*) were implemented using fixed values for $\boldsymbol{K}$ and $\boldsymbol{D}$ throughout the entire task execution. The diagonal coefficients of $\boldsymbol{K}$ were set to a low (resp. high) value in the RF (resp. RL) condition, as listed in Tab. I (all 6 coefficients have the same value). The coefficients of $\boldsymbol{D}$ were computed from $\boldsymbol{K}$ and the Cartesian mass matrix using factorization design [29], [16].

2) Collaboration conditions: The two collaboration conditions (RR: *reciprocal stiffness*, RM: *mirrored stiffness*) were defined and implemented based on the work by Peternel *et al.* [16]. In both cases, the robot Cartesian stiffness was adjusted online throughout the task depending on the human co-contraction index icc (Eq. 1). The human wrist stiffness trend $c_h(t)$ was approximated in this work as proportional to icc using the sigmoid function

$$c_h(t) = b_1 \frac{1 - e^{-b_2 icc(t)}}{1 + e^{-b_2 icc(t)}} \in [0, 1] \tag{3}$$

where $b_1, b_2 \in \mathbb{R}$ define the amplitude and shape of c_h, and were determined experimentally to reflect the actual operational range of the icc of a participant during the task execution.

For the *reciprocal stiffness* behavior (RR), the robot stiffness $\boldsymbol{K}$ was computed as:

$$\boldsymbol{K}(t) = \boldsymbol{K}_{cte} + \boldsymbol{S}\Big(\big(1 - c_h(t)\big)(\boldsymbol{K}_{\max} - \boldsymbol{K}_{\min}) + \boldsymbol{K}_{\min}\Big) \tag{4}$$

where $\boldsymbol{S}$ is a selection matrix that defines the axes where the stiffness is modulated, $\boldsymbol{K}_{min}$ and $\boldsymbol{K}_{max}$ contain the maximum and minimum desired stiffness for those axes, and $\boldsymbol{K}_{cte}$ contains a constant stiffness for the axes that are not modulated (the numerical values of these matrices' diagonal coefficients are summarized in Tab. I while the value of $\boldsymbol{K}_{cte}$ has been chosen following [16]). In this experiment, the translational stiffness in the horizontal plane was modulated, while the vertical translational stiffness was constant. In this condition, the robot behaves as a leader if the human is compliant, whereas it effectively cedes the autonomy of the task to the human when the human co-contracts.

For the *mirrored stiffness* behavior (RM), $\boldsymbol{K}$ was:

$$\boldsymbol{K}(t) = \boldsymbol{K}_{cte} + \boldsymbol{S}\Big(c_h(t)(\boldsymbol{K}_{\max} - \boldsymbol{K}_{\min}) + \boldsymbol{K}_{\min}\Big) \tag{5}$$

In this condition, the more the human co-contracts, the higher the robot's stiffness is.

3) Robot reference trajectory: The robot reference trajectory $\boldsymbol{x_d}$ was predefined offline for the RL, RR and RM conditions. The desired end-effector orientation and vertical position remained fixed for the entire task, while the trajectory in the horizontal plane was defined from straight lines and a parabolic curve (Fig. 1). In the RF condition, $\boldsymbol{x_d}$ was

Robot role	**Stiffness Profile**	$\boldsymbol{K}_{\min}$ $(N.m^{-1})$	$\boldsymbol{K}_{\max}$ $(N.m^{-1})$	**Reference Trajectory**
Follower	$\boldsymbol{K} = \boldsymbol{K}_{\min}$	100	-	No
Leader	$\boldsymbol{K} = \boldsymbol{K}_{\max}$	-	1000	Yes
Reciprocal	$\boldsymbol{K}(t) \propto (1-c_h)$	100	1000	Yes
Mirrored	$\boldsymbol{K}(t) \propto c_h$	100	1000	Yes

TABLE I

DEFINITION OF THE ROBOT STIFFNESS PROFILE AND REFERENCE TRAJECTORY FOR THE FOUR DIFFERENT CONDITIONS.

set equal to the robot Cartesian pose at the previous timestep, which, associated with low stiffness, made the robot very compliant. The duration of the reference trajectory was tuned experimentally and set to 25 seconds, which corresponded to a comfortable pace for users.

C. Statistical analysis

In this work we measured the following dependent measures: the RMS value over a trial of the human co-contraction index, the number of contacts between the pipe and the tubes, and the score of each item in the questionnaire. The co-contraction index and number of contacts were evaluated for every single trial. To get rid of any short-term learning effect that might happen in the early trials, we calculated linear regressions between the trial number and these dependent measures to identify when participants reached steady state performance. Regressions were calculated for each of the four conditions, iteratively for the last 15, 14, 13 trials, and so forth until the slopes were not significantly different from zero (i.e. the 95 % intervals did include zero). This occurred when the regression was computed over the last 11 trials (i.e. excluding the first 4 trials). Hence, the first 4 trials of each condition were excluded from the subsequent analyses. In addition, since only steady-state performance was considered, each metric was averaged over the last 11 trials to obtain one single data point for each participant and condition.

Co-contraction index was checked for normality with a Shapiro-Wilk test and then analyzed with a one-way repeated-measures analysis of variance (ANOVA) with *condition* as a within-subject factor and *participant* as a random factor. Pairwise multiple comparison post-hoc tests with Bonferroni corrections were conducted when a significant effect of *condition* was detected by the ANOVA. Questionnaire scores and number of contacts were analyzed with non-parametric Friedman tests given the nature of the data. Post-hoc tests were conducted when a significant effect of *condition* was detected. A significance level of 5 % was adopted for all statistical tests.

V. RESULTS

A. Pipe–tube contacts

Fig. 3a displays the distribution of the number of contacts between the pipe and the tubes for all 4 conditions. The Friedman test revealed a significant effect of the *condition* factor ($\chi^2(3) = 16.15$, $p = .001$). Post-hoc tests indicated a significant difference between RF and all other conditions

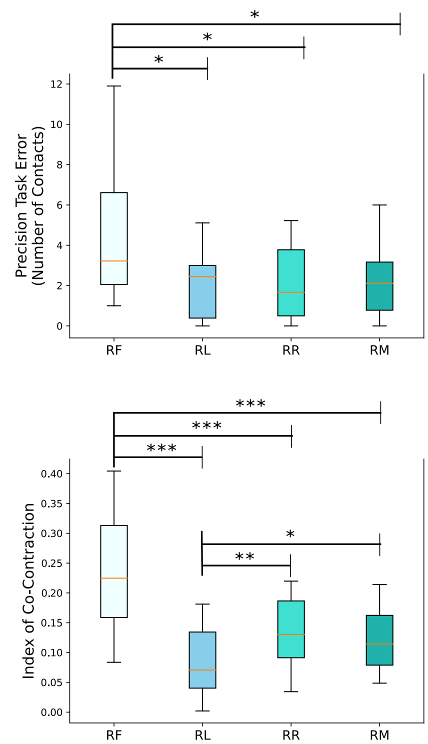

Fig. 3. Objective performance metrics in the 4 conditions. RF: *robot follower*, RL: *robot leader*, RR: *reciprocal stiffness*, RM: *mirrored stiffness*. *Top:* Task errors (number of contacts). *Bottom:* ICC of the participants.

(RF–RR: $p = .026$, RF–RL: $p = .03$, RF–RM: $p = .045$). The number of contacts (errors) was larger when the humans lead the task (RF condition) where they could not benefit from the robot position accuracy. All 3 other conditions were not statistically different.

B. Human co-contraction index

Fig. 3b displays the distribution of the co-contraction index for all 4 conditions. The ANOVA revealed a significant effect of the *condition* factor ($F(3, 42) = 27.8$, $p < .001$) on the co-contraction index. Post-hoc test revealed a significant difference between RF and all other conditions (RF–RL: $p < .001$, RF–RR: $p < .001$, RF–RM: $p < .001$), between RL and RR ($p = .009$) and between RL and RM ($p = .03$). Co-contraction was the largest when the human lead the task (RF condition), and the smallest when the human was following the robot (RL condition). Co-contraction was intermediate in the two collaborative conditions (RR and RM).

C. Questionnaire

Fig. 4 displays the distribution of the scores for the questionnaire. The Friedman tests revealed a significant effect of the *condition* factor for question Q1 (*How easy was it to do the task with the robot?*) ($\chi^2(3) = 15.3$, $p = .003$), but not for Q2 (*How much did the robot prevent you from doing the task the way you want?*) ($\chi^2(3) = 2.65$, $p = .5$). For Q1, post-hoc tests indicated a significant difference between RL and RF ($p = .004$) and RL and RM ($p = .01$), with

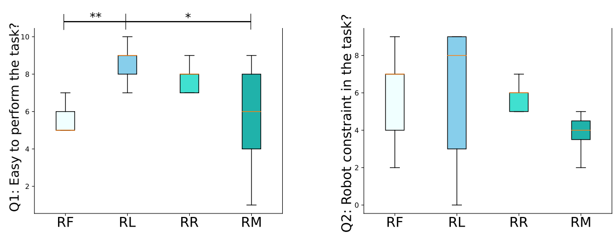

Fig. 4. Questionnaire results in the 4 conditions. Q1: 1 = not at all easy, 10 = very easy. Q2: 1 = much prevented, 10 = not prevented at all.

participants feeling the task easier to perform when the robot was leading (RL condition). The other comparisons did not reach significance. While there was no statistical difference between the two collaborative conditions (RR and RM), there is a trend towards a preference for the reciprocal strategy (RR) since the median was higher (i.e. the task was perceived as easier) with RR compared to RM. The responses were also more homogeneous among the participants with the RR strategy. For Q2, trends suggest that participants had very diverse opinions on how the robot was hindering them in the 2 cooperation conditions (RF and RL), whereas the opinions were more similar across participants in the 2 collaboration conditions (RR and RM).

VI. Discussion

In this study, we investigated the performance, human arm stiffness and human perception in different cooperative and collaborative modes of a human–robot co-manipulation task (question 1: cooperation vs. collaboration; question 2: mirror vs. reciprocal behavior in collaboration). In a previous work on human–human dyads performing the same task, we observed an improved performance at the cost of a higher effort when using collaborative strategies over cooperative ones. In this context, we investigated if the same results are observable in the human–robot scenario (question 3).

A. Cooperation or collaboration?

We expected the *robot leader* (RL) condition to be the most accurate in terms of task errors (number of contacts) because the robot had a reference trajectory that could precisely accomplish the task. In this case, if the human complied with the robot's actions, without adding perturbations, then the risk of task errors would be close to zero. The RL condition indeed led to fewer errors than when the human was entirely leading the task (RF condition). But both collaboration conditions (RR and RM) actually exhibited a performance as good as the when the robot was leader (RL). Thus, when collaborating with the robot, the human seems to fully benefit from its accuracy. This is similar to the human–human experiment, where the collaboration condition resulted in fewer errors than in cooperation conditions where one human was acting as leader and the other as follower. (Fig. 3)

Regarding co-contraction, which is linked to the physical effort induced by the task, the highest ICC values occured when the human was the leader (RF). Indeed, in this condition the human has both to drive the overall motion and is entirely responsible for the task accuracy. In addition, even if the robot is following the human in a very compliant mode, it is not entirely transparent. Hence, some human effort is also needed to compensate for the lack of transparency of the robot. In the *robot leader* (RL) condition, the ICC was logically the lowest, as the human only had to be compliant with the robot motion. This result is aligned with the subjective feedback from the participants, who reported the task was the easiest to perform in RL (Q1 of the questionnaire). Participants often reported that they "were just trying to relax and follow the robot" applying minimal effort. This finding is aligned with our observations of the human–human experiment, where ICC was the lowest for the follower agent in cooperative condition. The ICC values of both collaborative conditions (RR and RM) were in between RF and RL, though closer to the RL (i.e. human follower) condition. This result somehow differs from the human–human scenario, where the ICC values were similar between the collaborative condition and the leader condition. This could be due to the lack of transparency of the robot, which induced higher ICC when the human was leader (RF).

Considering both the task precision and the human effort, the *robot leader* (RL) seems the best condition. However the low ICC level and the subjective feedback in RL condition point out a possible risk of "disengagement" from the task execution: if humans passively follow the robot across several repetitions of the task, they may risk progressively losing awareness of the task and their surroundings. Should something unexpected occur, the limited awareness decreases the chance of a prompt reaction, and in addition, the high robot stiffness of the RL condition strongly prevents the human from correcting the robot. Such risk of disengagement is especially detrimental, as a realistic case of human–robot interaction with a robot leader would likely correspond to a scenario where the human has a supervisory role and needs to intervene in punctual but critical occasions. Hence concentration and awareness are key. In addition, the large distribution of answers to Q2 (how much the robot was perceived as constraining) suggests that some participants did not like the *robot leader* condition, possibly because they could not execute the task the way they wanted to.

Conversely, the intermediate ICC values of both collaboration conditions (RR and RM) have the advantage of limiting the risk of disengagement while requiring only a limited physical effort. In RR and RM, the force exerted by the operator allows him to assert his will over the robot and to communicate via the haptic channel [30]. Since the collaboration conditions were also associated with a low number of errors (similar to RL mode), the answer to question 1 is that collaboration seems to be more recommended than cooperation for human–robot co-manipulation. This result is partly aligned with the one of the human–human experiment, where collaboration yielded better performance than cooperation, at the expense of larger ICC values. However, the experimental context is different: in human–human dyads, the desired trajectory of the (human) partner is less predictable and may vary across trials; it also does not necessarily guarantee efficiency or accuracy for completing the task. Conversely, in the human–robot experiment, the human participants were aware that the robot had a fixed reference trajectory that enabled them to accomplish the task.

Following these results, we argue that giving some degree of autonomy to the human is overall positive. The human can still benefit from the robot's assistance, especially if the robot has a reference task trajectory. Furthermore, in collaborative conditions, robot compliance can leave the necessary degree of maneuver to the human to correct the task when needed, maintaining the task engagement, without degrading the task performance. In addition, in cooperative conditions, participants had very variable opinions to the question of whether the robot was interfering with executing the task in their own way (Q2 of the questionnaire). Conversely, they judged that the hindrance was relatively acceptable with more homogeneous answers in the collaborative conditions. This is an important element in favor of collaborative robot behaviors for industrial applications: if robots must be used by a diverse population of workers, it is possible to expect a more consistent attitude towards collaborative rather than cooperative robots.

B. Preference for collaboration with reciprocal impedance

In terms of statistical results, there was no significant difference between the two collaborative conditions (RR and RM) for the number of errors, the co-contraction index, nor the responses to the questionnaire. But interestingly, in informal feedback, the majority of participants reported preferring the reciprocal strategy (RR) over the mirrored one (RM). This is aligned with the trend in the questionnaire answers, where the median value is higher (i.e. more positive) for both questions in the reciprocal condition.

The preference for the reciprocal condition contrasts with our expectation from the human–human study, where collaborators exhibited high arm co-contraction as if they were both trying to lead, i.e. closer to a mirrored impedance strategy. A difference between both experiments is the processing time necessary to adjust the robot stiffness in the human–robot study. The robot stiffness was adjusted based on the human co-contraction index estimated online from EMG data. But the acquisition and processing of EMG data induce some delay in the robot stiffness adaptation, which might affect the human response. However, this delay was limited, and humans also exhibit sensory-motor delay. Plus, no oscillatory behavior was observed in any of the collaboration strategies. It is therefore unlikely that the difference between the human–human and human–robot results are caused by a delayed robot adaptation. In hindsight, humans might prefer to interact with a "docile" robot that complies with human behavior, rather than competing with a robot that stiffens as the human does: lowering the stiffness when the human co-contracts may enforce the human feeling of being in control (empowerment), which has been frequently reported in the literature as one of the main drives for accepting and trusting a robot [4], [31], [3]. The reciprocal collaborative strategy also has the advantage of being more conservative concerning the passivity of the system, with notable safety implications [32]. The answer to question 2 is thus that the robot should better have a stiffness behavior reciprocal to the user's. Regarding question 3, the findings from the human–human study only partly transfer to the human-robot case.

C. Limits of the study

Our study nevertheless has some limitations, and our results should be considered carefully. First, the study was conducted with participants from the university environment, and while few participants were familiar with robots, the results cannot be generalized to a generic population, especially with industry workers who may have different attitudes when interacting with a robot [3]. Second, the co-manipulation task was simple and the manipulated load was small and light. We do not know if our results can be generalized to other co-manipulation tasks involving large and heavy loads, a situation that is often found in manufacturing where robots physically assist workers (e.g., manipulating car parts, such as wheels [33]). Third, the performance of each condition might change with more training and expertise with the robot and the task. We already accounted for the source of bias due to learning by not including the initial trials in our analysis. However, the RF condition, which exhibited the worst results in terms of number of errors and co-contraction index, was always executed first (for the reasons explained in Section IV-A.3, which in future work could be overcome by performing a separate calibration phase). So the order of the conditions might partly explain the lowest performance of the RF condition. Yet, participants reported that it was not easy to do the task with the robot in this condition, and our intuition is that this is mostly because the robot was not entirely transparent. Overall, it is possible that interactions over hundreds of trials may lead to lower ICC levels and fewer errors. Future studies should investigate whether there is a significant learning effect for longer interactions and whether this learning process is user-specific: this knowledge will be critical to recommend suitable training to workers that collaborate with robots on a particular workstation. A last bias is the task duration. In the *robot follower* condition, participants were not constrained by a robot reference trajectory, and hence could perform the task at their own pace. Conversely, in all 3 other conditions, the robot reference trajectory guided, more or less firmly, the task duration. While the duration of the reference trajectory was chosen to be comfortable according to pilot tests, in the actual experiment participants were much faster when not constrained by the robot trajectory (average task duration: 13 s for RF, vs. between 22 and 23 s for RL, RR and RM). This difference between the human natural pace and the robot pace might have impacted how much the robot was perceived as a constraint in RL, RR and RM conditions. In future experiments, we will investigate solutions involving variable speed for the robot reference trajectory, as in [34].

VII. CONCLUSION

In this study, we investigated whether it is preferable and more performing for a robot to behave as a cooperator (leader or follower) or collaborator (adaptive impedance) during a co-manipulation task with a human, and what kind of adaptation strategy (mirror or reciprocal) is better in case of collaboration. We also compared with previous results of human dyads performing a similar task, to understand how much human behavior observed when working with another human transfers to working with a robot. Our results suggest that a robot collaborator is preferable to a robot cooperator (leader or follower), similarly to what we observed for human dyads. Collaboration showed a good compromise between task performance and human effort, while limiting the risk of human disengagement. However, the way humans collaborate with the robot differs from when collaborating with another human. Within collaboration, the robot should preferably adopt a reciprocal impedance strategy, adapting its stiffness inversely to the human arm co-contraction, contrary to what human dyads do. While not strictly superior in terms of performance, the reciprocal strategy was nevertheless preferred by humans when working with the robot. Our results are relevant for the design of human–robot collaborative workstations. They also evoke new questions to further understand human behavior, precisely the human arm impedance, during joint work with humans and robots.

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