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The effects of role transitions and adaptation in human–cobot collaboration

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Abstract

Collaborative robots (cobots) have the potential to augment the productivity and life quality of human operators in the context of Industry 4.0 by providing them with physical assistance. For this reason, it is necessary to define the relationship between humans and cobots and to study how the two agents adapt to each other. However, to the best of our knowledge, literature is still missing insight into how humans perceive and react to changes in the cobot behavior (e.g. changes in the learned trajectory and in the role the robot assumes). Specifically, a study of how humans adapt to changing roles and control strategies of collaborating robots is missing. To fill this gap, we propose a human study in which 16 participants executed a collaborative human–robot sawing task where the cobot altered between three different control strategies. We examined human adaptation when cobot suddenly changed the control strategy from one to another, resulting in six experimental conditions. The experiments were performed on a setup involving Kuka LBR iiwa robotic arm. The results suggest that transition influences movement performance in the early stages and at steady state, subjects prefer to abandon modes that require more effort and they adapt faster to energy-demanding modes. Finally, for the specific task we studied, subjects tend to prefer collaborative modes to ones in which the robot assumes a fixed role.

Keywords Collaborative robots · Adaptation · Human–robot physical interaction

Introduction

Industry 4.0 is a new manufacturing paradigm involving novel production technologies in order to improve worker's conditions and to increase productivity and quality (Nardo et al., 2020). Among these technologies, robotics solutions have the potential to increase productivity and the working conditions of human operators (El Makrini et al., 2019). Machine productivity and human flexibility have notably been combined in a concept called human–robot collaboration (HRC) (Kumar et al., 2020). Robots built with this intent are called collaborative robots or, more commonly, *cobots*. Moreover, cobots implementations aim to improve safety and performance while at the same time facilitating more interesting responsibilities for human workers and increasing productivity growth (Maddikunta et al., 2022) by sharing knowledge between robots and humans and by learning from others (Ngoc et al., 2022).

In many HRC scenarios, humans' cognitive abilities are used to supervise the cobots' physical capabilities (Faccio et al., 2023a) or to teach the robot how to perform a specific task by demonstration (Ye et al., 2020). When physical human–robot interaction (pHRI) is present, it is often treated as a strict asymmetric relationship leaving low decision power to the robot (Jarrasse et al., 2014) and much attention is devoted to the safety during the interaction (De Luca et al., 2006). This is mainly due to the forces the robot is able to exert, which must be monitored to maintain safety for the operator as the

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two perform the operation together (Faccio et al., 2023b). Thanks to improved sensing and control abilities, cobots gained major awareness in more recent HRC implementations (Selvaggio et al., 2021). This allows them not only to share the same workspace with human operators but also to provide physical assistance to reduce efforts and more generally to improve ergonomics in shared tasks (Ajoudani et al., 2018b). For instance, control algorithms have been designed to reduce human overloading joint torques coordinating the two partners in joint tasks (Peternel et al., 2017a) which required redefining the relationship between the human and the cobot and particularly the role of each concerning the collaborative task.

In the advanced paradigm of collaboration, typical of Shared Autonomy (Selvaggio et al., 2021), the collaborative robot is capable of adapting its level of autonomy based on its own understanding of human behavior and of the environment. Several aspects of collaboration have been investigated (Faccio et al., 2023a): the communication channel between human and cobot (Liu et al., 2022), the experience of the operator in the task to be performed (Erden & Billard, 2015) and individual behavior characteristics (Robert, 2018). Nevertheless, a fundamental question for this kind of collaboration is how the two agents adapt to each other across the tasks. In fact, if the robot were able to predict how a subject would adapt to a given policy, it could vary its policy with the intent of accelerating adaptation (in case the equilibrium condition was good) or conversely guide it to another equilibrium condition.

Human–machine adaptation is a widely studied field even beyond pHRI (Gallina et al., 2015), implementing adaptive control schemes which conform to an unknown gain of the human (Dong et al., 2020). Adaptation could be integrated by changing the cobot policy when thresholds of safety have been reached. For instance, Peternel et al. (2018) proposed a method for HRC where the robot behavior is adapted online to human motor fatigue. Similarly, in Cacace et al. (2022) the cobot on-line infers whether the human guidance is aligned to the planned activities and adapts its cooperative behavior accordingly. In other situations, adaptation can be used to solve problems in which neither the human nor the robot is able to solve the problem on their own (Shafti et al., 2020).

Many of these works presented control algorithms that adapt and change the cobot policy during collaboration with humans. However, to the best of our knowledge, we lack knowledge of how humans perceive and react to changes in cobot behavior. Specifically, little is known about how humans adapt to changing roles and control strategies of collaborating robots during pHRI. We think this knowledge is important because it allows the robot to predict how a subject would perform in the short period (before adaptation) and in the long period (when the adaptation is reached). Knowing this the robot's policy can change to modify situations harmful to the subject.

To fill this gap, we propose a human study in which 16 participants executed a collaborative human–robot sawing task where the cobot altered between three different control strategies (human-leader, human-follower, and reciprocal). In human-leader mode, the human guides the execution of the collaborative task, while the cobot follows. Vice versa, in human-follower mode, the cobot leads the execution, while the cobot follows. Finally, in reciprocal mode, the human and cobot behaviors are reciprocal in terms of the phase of operation. We examined human adaptation when the cobot suddenly changed the control strategy from one strategy to the other, resulting in six experimental conditions. The experiments were performed on the Kuka LBR iiwa robotic arm.

The aim of our study is to try to answer some of the questions not addressed in the literature. In our previous human studies (Vianello et al., 2022; Peternel et al., 2016) we observed that when there is a change in the robot behavior (robot gaining autonomy) the human needs some time to adapt to that new behavior. During this adaptation period, the performance of the task and the effort to execute it may be affected. For this reason, in this paper, we want to assess how switching is perceived, with both objective and subjective metrics. We also ask how collaboration performance is affected in the short and long term. Finally, we think it is interesting to assess how long subjects need to adjust to a strategy. We addressed the following questions:

- **(Th1)** *How the switching between modes is perceived by the human? Is the task performance influenced in the first iterations of the task after the switching?*
- **(Th2)** *Does a past transition influence the collaboration even after a steady state is reached?*
- **(Th3)** *Do humans prefer some transitions with respect to others?*

We also observed the data collected before the mode switching happened and we used it to compare the three different modes. This analysis is part of a series of works (Kheddar, 2011; Jarrasse et al., 2014) that seek to understand what role the robot should assume when physically interacting with the human (constant/dynamic, cooperation/collaboration, low/high autonomy). For this reason, we addressed the following questions:

- **(Th4)** *Do humans adapt faster to some modes with respect to others?*
- **(Th5)** *For the specific task studied in this work, is there a preferred mode of interaction among human-leader* (***L***), *human-follower* (***F***), *reciprocal* (***R***)

We answer all these questions for this specific task from both a point of view of objective measures and from a point of view of human perception (subjective scales).

Related works

Roles in pHRI: cooperation and collaboration

The concept of pHRI combines human skills, such as versatility, with the physical advantages of the robot (Kumar et al., 2020). Two kinds of interactions are interesting pHRI: cooperation and collaboration (Jarrassé et al., 2012). In cooperation, the roles of the two agents (human and robot) are fixed while, in collaboration, they adapt during the task execution. Human-leader/robot-follower role allocation is typically the preferred strategy in many cooperation scenario (Losey et al., 2018): in this case, the cobot handles secondary tasks, such as rejecting disturbances (Hogan, 1984), or sustaining forces and positions in different axes from the ones controlled by the human (Wang & Li, 2010). The role of the cobot determines the impedance behavior at the interaction point. During the leader behavior, the cobot controller can minimize the errors for the actual trajectory and the desired one (high-impedance), whereas during follower behavior it minimizes the forces applied at the contact point with the human operator (low-impedance). By varying the stiffness-damping parameters, the behavior of the cobot can be modified between these two extremes (Kheddar, 2011).

Even though cobot fixed roles meet great success in several applications such as robotic surgery (Rahal et al., 2020) and telemanipulation, there are instances in which collaboration, and thus, adaptive or variable roles could be preferred (Jarrasse et al., 2014). Within this context, Agravante et al. (2019) interpolate between a humanoid robot's behavior from a total leader to a total follower. To facilitate effective collaboration in pHRI and switch roles, the robot should be able to detect human intent online. Khoramshahi and Billard (2020) propose a method to automatically detect when a human coworker is physically trying to guide a robot that is executing an autonomous task. After the intent detection, the robot switches into follower mode and only goes back to leader mode when the human stops correcting the robot.

One method widely used in the literature to modify the robot's impedance profile (and thus the role) is the so-called *tele-impedance*, namely the transferring of human impedance to the robot (Fani et al., 2018). Peternel et al. (2017b) presented two robot role allocations (reciprocal and mirrored) based on the concept of tele-impedance. 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). The same authors (Peternel et al., 2018) proposed a control implementation of the two roles for human–robot collaboration where the robot behavior is adapted online using electromyography (EMG) signals. The main advantage of using this type of sensor is that you can directly estimate the forces exerted by the human and separate them from those exerted by the surroundings (Bednarczyk et al., 2022).

While these works have demonstrated extensively how the use of variable impedance profiles can improve collaboration, little is known of how the human operator adapts to changes in robot roles.

Adaptation of roles in pHRI

A classical HRC strategy is to design cobot policies that adapt to humans (one-way adaptation). In (Li et al., 2015), the robot is able to adjust its own role according to the human's intention to lead or follow. Cherubini et al. (2016) alternate the leader and follower roles of a robot in a pHRI application for industrial assembly tasks according to visual and haptic cues by the human co-worker. Peternel et al. (2018) used tele-impedance to set the robot strategy and switch between roles when a given amount of fatigue is reached by the human. Other work proposes an adaptive control schemes in which the robot adapts its policy according to estimated forces (Dong et al., 2020).

In more recent work, it was hypothesized that better collaborative approaches can be designed by also considering how humans change their policy by interacting with the robot (Gallina et al., 2015). Nikolaidis et al. (2017) introduced a formalization for mutual adaptation between a robot and a human in a collaborative task. In a similar way, the study in (Shafti et al., 2020) presents a reinforcement learning algorithm able to solve a human–robot task in which neither the human nor the robot is able to solve the problem on their own. Ikemoto et al. (2009) showed the importance of a bilateral learning process that takes place in both partners. Other works consider the evolution of the human trust in robot (Chen et al., 2020) and the robot's persuasive ability (Saunderson & Nejat, 2022) to maximize long-term team performance.

To design the robot action which maximizes the expected reward, it is necessary to model the human behaviour (Wilcox et al., 2013) or, alternatively, the human–robot team behaviour (Nikolaidis & Shah, 2013). Nikolaidis et al. (2017) integrated the human ability to adapt to robot actions, defined as adaptability, to predict human actions in a human–robot collaboration scenario. Saunderson and Nejat (2022) proposed to use Adaptive Persuasive Systems to acquire user information, update user models and adapt their persuasive approaches to the human operator. Chen et al. (2022) use social projection theory to learn human models from human demonstrations. In addition, it should be considered that different individuals may have different behaviors. For this reason, Nemlekar et al. (2021) divided into cluster subjects accordingly to their preferences.

All the aforementioned works rely on some human behavior model that is used to determine the robot's policy of adaptation. However, these models lack information about how humans adapt to changes in the robot's behavior. To create more accurate human models, we believe human studies in pHRI that compare different robot policies and observe how the human adapts to these given policies are critical (Vianello et al., 2022). In particular, the impact of changes in robot control policies during the collaboration was not yet examined. For this reason, in this work, we examine how humans adapt when the robot suddenly changes the collaborative control strategy.

Methods

The aim of this study is to investigate how humans react and adapt to changes in cobot control modes during a collaborative task (**Th1**, **Th2**, **Th3**). Such changes are often necessary for collaborative robotics applications when different functionalities are required for task execution.

To investigate how humans adapt to changing policy, we conducted an experiment in which human participants performed a collaborative sawing task with a cobot under different conditions. Three control strategies were defined for the cobot end-effector impedance: human-leader (**L**), human-follower (**F**) and reciprocal (**R**). In human-leader mode, the human guides the execution of the collaborative task, while the cobot follows. Vice versa, in human-follower mode, the cobot leads the execution, while the cobot follows. Finally, in reciprocal mode, the human and cobot behaviors are reciprocal in terms of the phase of operation.

16 healthy adults took part in the experiment (4 females and 12 males, aged 24–30). 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 prior to starting the experiment. The study was approved by TU-Delft's ethical committee and was conducted following the Declaration of Helsinki (PP, 1964).

Each of the participants received instructions on the task to be performed, a description of the three modes, as presented in "Experimental setup and protocol" section, and was informed about the presence of a switch from one mode to another during each trial. However, they were not told what the two modes would be and when the switching would happen. They had to figure out which mode the cobot was executing, and how to adapt to the new one.

We are aware that our work has some limitations like the use of participants from the university environment and the choice of the sawing task (simple and common). In this sense, we do not know if our results can be generalized to other tasks involving large and heavy loads with movements on the three dimensions. Nevertheless, we think that our study provides a fundamental understanding of how to manage the robot controller transitions in a seamless manner.

Experimental setup and protocol

We selected a collaborative human–robot sawing task that requires both complex physical interactions and good coordination between the agents (Fig. 1). The task consists of alternating phases where the human pushes the saw (while the cobot pulls) and phases where the human pulls the saw(vice versa, the cobot pushes). The movement must be performed along the entire length of the saw (45 cm). Performing one trial takes 2 s on average. A metronome is used to help subjects keep a constant frequency of task execution. Constant frequency helps us to standardize the experiment among subjects to make data comparable also in the case when the human is the leader and so no hint on the frequency comes from the cobot. Participants face the cobot and hold the saw with their dominant hand, while the other side of the saw is attached to the cobot end-effector. Figure 1 shows the setup.

The cobot is controlled using three different control conditions (**F**, **L**, **R**) which are specifically adapted to the sawing task. In "Human-follower" (**F**), the human stabilizes the saw vertically, while the cobot does all the movement of the saw back and forth in the horizontal direction. In "Human-Leader" (**L**), the human moves the saw back and forth, while the cobot only stabilizes the saw at its own side. In "Reciprocal mode" (**R**), the robot replicates the standard way humans do the two-person sawing: both agents are only pulling the saw, and not pushing. The pulling is exchanged in the following manner. When humans pull the saw to their side, the cobot starts pulling it back to its side, and vice-versa. The reason not to pull is to not interrupt each other's activity (for example, in a two-person saw without the arc, the saw would bend, and the task would be interrupted). To express all the situations in which no previous mode has been executed (so the cobot is fixed), we used the terminology Nothing condition (**N**).

Each subject executed 6 trials; in each trial, two of the three cobot modes are executed. The first mode is executed for around ~ 2 m, then the transition happens and the cobot switches to the second mode for other ~ 2 m. Between each trial, the human rests and there is an allocated time to answer the questionnaire (~ 2 m) and time to recover (~ 3 m). The total amount of time for the entire experiment is ~ 1 h. The acoustic sound of the metronome tells the human when the trial starts. The metronome frequency does not change for

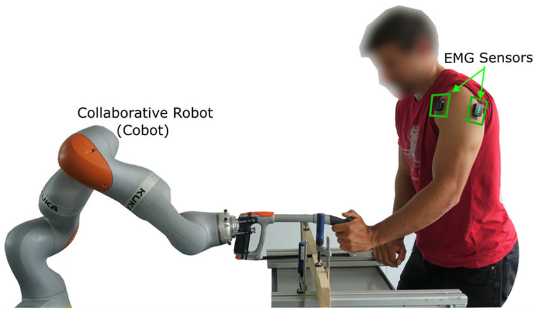

Fig. 1 The experimental setup: the cobot is semi-rigidly attached to the saw, likewise the subject grabs the saw from the other end. EMG sensors are attached to the subject to measure muscle contraction during movement

the full time of the task (even during the transition). The participant does not know which mode is executing nor when the transition happens. The six experimental conditions are presented in Table 1 and their order is presented randomly. One preliminary trial (in human-leader mode) of 1min is performed before each experiment to make the subject familiarize with the setup and the sawing task.

Cobot controls

The experiment was performed with a KUKA iiwa robot. The robot was controlled with a mixed force-impedance scheme. Impedance control allows to move the saw and easily implement different compliance behaviors. Force control allows the robot to maintain contact with the workpiece. Let the robot equation of motion be:

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau} - \boldsymbol{J}^{\top}\boldsymbol{F}_{int} \tag{1}$$

with $\boldsymbol{q} \in \mathbb{R}^n$, $\dot{\boldsymbol{q}} \in \mathbb{R}^n$, $\ddot{\boldsymbol{q}} \in \mathbb{R}^n$ respectively the joint angles and their derivatives (joint velocities and joint accellerations), $\boldsymbol{M}(\boldsymbol{q}) \in \mathbb{R}^{n\times n}$ the inertia matrix, $\boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}}) \in \mathbb{R}^{n\times n}$ 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 $\boldsymbol{F}_{int} \in \mathbb{R}^6$ the interaction forces and wrenches at the end-effector. A hybrid force/impedance controller was implemented following (Peternel et al., 2018). The force behavior was defined as

$$\boldsymbol{F}_{int} = \boldsymbol{F}_{for} + \boldsymbol{F}_{imp} \tag{2}$$

where the term $\boldsymbol{F}_{for}$ is related to the force task (i.e., in sawing is keeping contact with the wood) controlled by a PI controller

$$\boldsymbol{F}_{for} = \boldsymbol{K}_P^F \boldsymbol{e}_F + \boldsymbol{K}_I^F \int \boldsymbol{e}_F dt, \tag{3}$$

$$\boldsymbol{e}_F = \boldsymbol{S}_F(\boldsymbol{F}_a - \boldsymbol{F}_d) \tag{4}$$

where $\boldsymbol{K}_P^F$, $\boldsymbol{K}_P^F$ are the gain of the PI controller, while $\boldsymbol{F}_a$, $\boldsymbol{F}_d$ are respectively the actual and the desired force on the end-effector. The desired mechanical impedance at the end-effector is defined as:

$$\boldsymbol{F}_{imp} = \boldsymbol{K}(\boldsymbol{x_{ee}} - \boldsymbol{x_d}) + \boldsymbol{D}(\dot{\boldsymbol{x}}_{\boldsymbol{ee}} - \dot{\boldsymbol{x}}_{\boldsymbol{d}}) \tag{5}$$

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 three different robot behaviors described in "Experimental setup and protocol" section were implemented by changing the values and profiles of the $\boldsymbol{K}$ and $\boldsymbol{D}$ matrices, as explained in the next section. Only the translational stiffness and damping were modified across conditions, whereas the rotational part remained identical.

Robot role allocation

The two experiment conditions **L** and **F**, were implemented using fixed values for $\boldsymbol{K}$ and $\boldsymbol{D}$ throughout the entire task execution. The coefficient of $\boldsymbol{K}$ on the direction of the sawing was set to a zero value when the human leads the movement. When the human follows, the coefficient is set to a high value. The coefficients of $\boldsymbol{D}$ were computed from $\boldsymbol{K}$ and the Cartesian mass matrix using factorization design (Albu-Schaffer et al., 2003).

The "Reciprocal mode" **R** was defined and implemented based on the work by Peternel et al. (2017b). The robot's Cartesian stiffness is adjusted online throughout the task depending on the human shoulder stiffness trend $c_h(t)$. The human stiffness profile is estimated as in Ajoudani et al. (2018a) using the scaled mean of shoulder antagonist muscle contractions (A_1, A_2):

$$c_h = a\left(\frac{A_1 + A_2}{2}\right) \in [0, 1] \tag{6}$$

where $a \in \mathbb{R}$ defines the amplitude and shape of c_h, and is determined experimentally.

For the *reciprocal stiffness* behavior (R), $\boldsymbol{K}$ is:

$$\boldsymbol{K}(t) = \boldsymbol{K}_{const} + \boldsymbol{S}\Big(\big(1 - c_h(t)\big)(\boldsymbol{K}_{\max} - \boldsymbol{K}_{\min}) + \boldsymbol{K}_{\min}\Big) \tag{7}$$

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 $\boldsymbol{K}_{const}$ contains a constant stiffness for the axes that are not modulated. In this experiment, the translational stiffness in the direction of the sawing was modulated, while the other components were constant. In this condition, the robot behaves as a leader if the human is compliant, whereas it effectively

Table 1 Study design and experimented conditions: each subject performs the six experimental conditions, in which the cobot changes the mode from one to another

Experimental condition	Cobot controls	Modes conditions	Cobot control
1	F → L	1b	N → F
2	F → R		
3	L → R	2b	N → L
4	L → F		
5	R → F	3b	N → R
6	R → L		

Three modes were tested: human follower (F), human leader (L), and reciprocal (R). To express all the situations in which no previous mode has been executed (so the cobot is fixed), we used the terminology Nothing condition (N). The experimental conditions are tested in random order

cedes the autonomy of the task to the human when the human co-contracts.

The robot reference trajectory has been designed in Cartesian space between two points based on the required saw movement in the experimental setup. When the robot reaches one end-point, it then comes back to the other end-point. The orientation of the saw is kept constant throughout the movement. The duration of the reference trajectory was tuned experimentally and set to 2 s, which corresponded to a comfortable pace for users and was comparable to the previous studies on human–robot collaborative sawing (Peternel et al., 2017b).

Performance metrics

To evaluate the performance of the task execution and of the collaboration, we observed the following **objective metrics**. These performance metrics were calculated at each iteration of the task, whereas iteration is considered one round trip of the saw.

- M_1 **Length of the movement** makes it possible to verify that the movement is performed along the entire length of the blade. This value is assessed using the difference between the minimum value and the maximum value of the movement in the y direction. At best, the length of the movement is equal to the length of the blade ($45cm$).
- M_2 **Acceleration** gives an estimation of the smoothness of the movement and it is calculated with double derivation from the movement. We considered the mean of the absolute value of the acceleration. The position of the end-effector is assessed using the direct kinematics model of the robot. These values are recorded using $rosbag$ collecting the ros messages sent by the kuka control software.
- M_3 **Co-Contraction index (ICC)** provides an estimation of the human effort. Co-Contraction index is the minimum value of antagonist muscles. This value is usually associated with human stiffness (Gribble et al., 2003). The value is calculated as the mean value of all the ICC over one trial.
- M_4 **Force applied to the robot** is also a measure of human effort. It is calculated using the robot torque sensors ($F_{ext} = J^{-T}\tau_{ext}$). We considered the mean value of the absolute value of the force only in the direction of the sawing (namely y axis) because we do not notice big forces in the other directions. Also in this case we collect the ros messages sent by the kuka controller using $rosbags$.
- M_5 The **Error on the reference position** gives us an idea of how much the subjects differ in motion from the trajectory proposed by the robot. It is important to note that in the human leader mode (L) the subject has no clue what the trajectory indicated by the robot is. This justifies the use of the metronome as a tool to equalize the comparison between different modes.
- M_6 **Fourier** To compare the smoothness of each movement, we compute the sum of the frequencies minus the principal frequency using the Fourier transform of the movement (Bracewell & Bracewell, 1986).

Moreover, to evaluate the human adaptation to a given mode after the transition happens we calculate the number of transitions necessary to reach a steady state for the human. The next section ("Statistical analysis" section) will present how we consider that a steady state is reached.

We also evaluate how the subjects perceived each experimental condition. This **subjective metric** is composed of a set of questions. After each trial, the subjects answer three questions related to how they perceived the transition between modes:

1. *Did you recognize the* 2 *modes?* This question was added to stimulate the subject to explore the experimental condition they are testing and thus engage more in the collaboration.
2. *The transition between the two modes was challenging.*
3. *I felt that the performance in collaboration improved after mode transitioning.*

After each experiment, they are additionally asked to fill in a questionnaire related to individual mode, with the following questions, with answers on an X-items Likert scale.

1. *The mode was engaging*
2. *The mode was demanding*
3. *The mode required high cognitive effort*
4. *The mode required high physical effort*
5. *The mode was boring*

Moreover, we included the Van der Laan questionnaire (Van Der Laan et al., 1997), which evaluates perceived usefulness and satisfaction for an experimental condition.

Statistical analysis

For each experimental condition, we analyzed two critical times: just after the mode-switching and when the steady state is reached. We decided to study the first trials after the transitions because during pilot experiments we observed that these are the more critical moments for the collaboration.

To identify when participants reached steady state performance, we use linear regression. Regressions were calculated for each of the six experimental conditions ($F\rightarrow L$, $F\rightarrow R$, $L\rightarrow R$, $L\rightarrow F$, $R\rightarrow L$, $R\rightarrow F$) and the "nothing-to-something" conditions ($N\rightarrow L$, $N\rightarrow R$, $N\rightarrow F$), in an iterative way for the last n trials, where n goes from N(number of trials) to zero. We repeated this procedure until the slopes were not significantly different from zero (i.e. the 95 % intervals did include zero). Since different performance metrics have different convergence times to steady state, we decided to take the last one to converge.

The data (both for the first trials and for steady-state conditions) were 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 (Dixon & Massey Jr, 1951). 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 the 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. Analyses were performed with python software.

Results

This section is composed of three main parts. First, we look into transitions between modes. Second, we examine modes on their own. Finally, we check the results of the subjective evaluation of both transitions and modes using questionnaires.

Transitions evaluation

Transitions between modes are evaluated in terms of progress and in terms of reaching a steady state.

Progression

We noticed that the progress of the performance metrics varies accordingly to the current mode and the one experienced in the past. We could observe that the average number of iterations necessary for the participants to adapt (and so reach steady state) varies across the experimental conditions ($R\rightarrow L$: 7, $F\rightarrow L$: 10, $L\rightarrow R$: 13, $F\rightarrow R$: 10, $L\rightarrow F$: 14, $R\rightarrow F$: 17).

Figure 2 we display the distribution of the metrics on the first iterations of the task after the mode switching. Fig. 2a displays the length of the movement, at best, the length of the movement is equal to the length of the blade (45 cm). We can observe that the more autonomy the robot has longer the movement. Figure 2b displays the accelerations during the movement execution. In this case, it is not easy to spot differences between the conditions. Figure 2c shows the distributions of the muscle co-contraction. This value is usually associated with human stiffness. Figure 2d exhibits the force the human is applying to the robot calculated using the robot torque sensors. Human force and human stiffness give valuable information about how much effort the subject is putting into performing the movement. In Fig. 2e are presented the distributions of the error in the reference trajectory. This value is useful to understand how much the subject could apply a different trajectory. Finally, Fig. 2f shows how smooth the trajectory is.

The ANOVA revealed a significant effect for the length of the movement ($p = 0.02$), co-contraction index ($p = 0.04$) force ($p < 0.001$), error on the reference position ($p < 0.001$) and smoothness of the movement ($p < 0.001$). For these cases, we executed Post-hoc test. For the length of the movement, we observed differences between $F\rightarrow L$ and $L\rightarrow F$ ($p = 0.02$) and values close to differences between $F\rightarrow L$ and $L\rightarrow F$ ($p = 0.06$) and $F\rightarrow L$ and $R\rightarrow F$ ($p = 0.058$). For co-contraction index between $R\rightarrow L$ and all the last three conditions ($p < 0.001$ for all the conditions) and a similar thing for $F\rightarrow L$ and all the last three conditions ($p = 0.03$, $p = 0.004$, $p = 0.01$ respectively). Concerning the force, we found significant differences between $R\rightarrow L$ and all the last four conditions ($p = 0.02$, $p = 0.02$, $p = 0.001$, $p < 0.001$ respectively) and a similar thing for $F\rightarrow L$ and all the last four conditions ($p = 0.012$, $p = 0.021$, $p = 0.003$, $p < 0.001$ respectively). Moreover, there are significant differences between $R\rightarrow F$ and the two con-

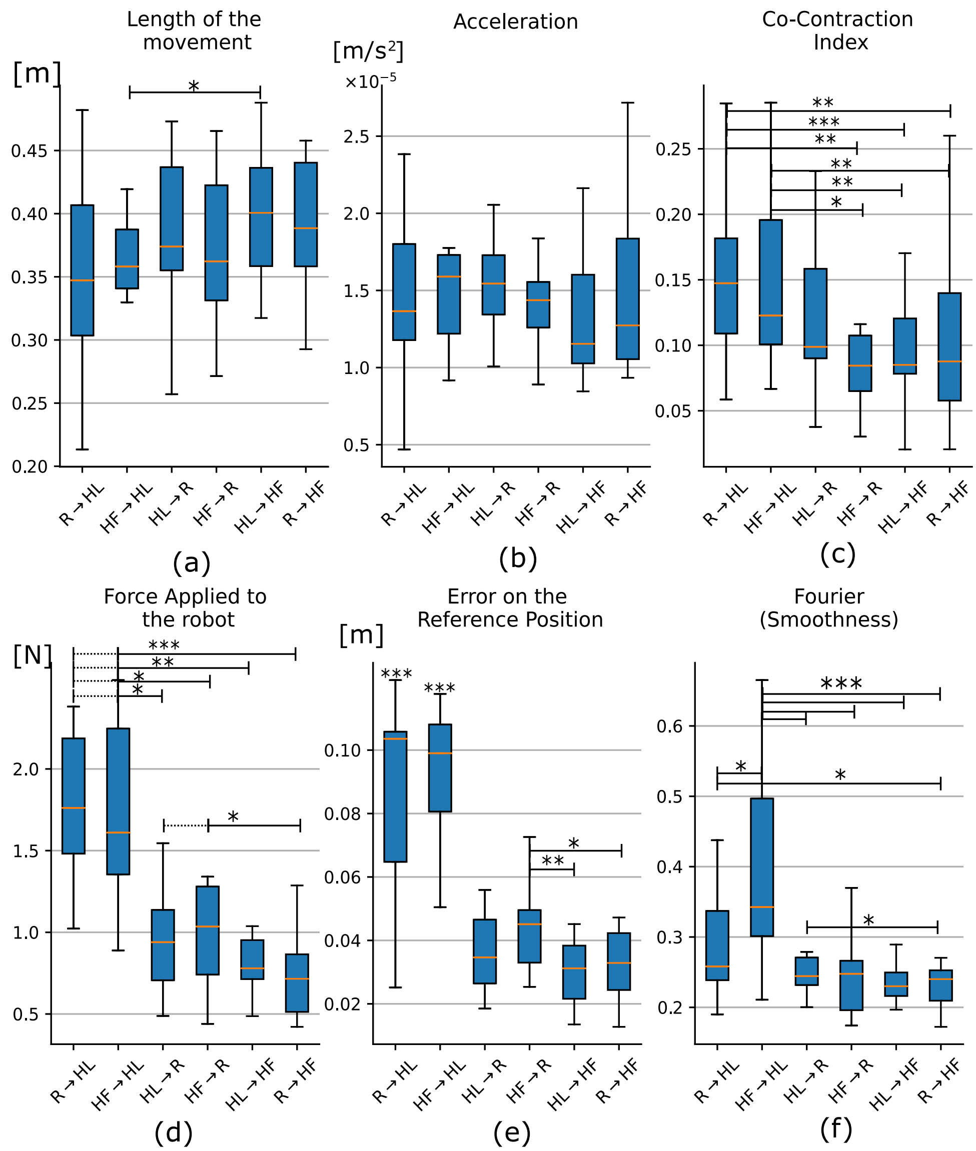

Fig. 2 Comparison of the experimental conditions at the first 5 iterations after the switching: (M_1) Length of the movement; (M_2) Acceleration; (M_3) Co-Contraction index of the subject and measured using EMG sensors; (M_4) Force applied to the cobot; (M_5) Error on the reference position; (M_6) Fourier. The six experimental conditions are the combinations of the three control modes: Human Leader(HL), Human Follower(HF) and Reciprocal(R). Stars above the boxplots indicate a statistically significant difference between conditions

ditions ending with R ($p = 0.01$, $p = 0.04$ respectively). Error on reference position reported differences between the conditions having L after the transition and all the others ($p < 0.001$); moreover, the experimental condition $F \rightarrow R$ presents statistical differences with the experimental modes ending with F ($p < 0.001$, $p = 0.006$). The smoothness of the movement suggest statistical differences between $R \rightarrow L$ and $R \rightarrow F$ ($p = 0.02$), $F \rightarrow L$ and all the others ($p = 0.015$ for the first condition and $p < 0.001$ for the last three conditions) and $L \rightarrow R$ and $R \rightarrow F$ ($p = 0.01$).

In summary, we observe that the transition heavily influences the collaboration.

Steady state

Figure 3 displays the distribution of the metrics on the steady-state iterations of the task and after the mode switching. The ANOVA revealed a significant effect for acceleration ($p = 0.02$), co-contraction index ($p = 0.008$), force ($p < 0.001$), error on the reference position ($p < 0.001$) and smoothness of the movement ($p = 0.004$). For these cases, we executed Post-hoc test. For the acceleration, we observed differences between $R \rightarrow L$ and $F \rightarrow R$ ($p = 0.02$), $R \rightarrow L$ and $L \rightarrow F$ ($p = 0.001$). For the co-contraction index, between $R \rightarrow L$ and the last four conditions ($p = 0.018$, $p = 0.006$, $p = 0.004$, $p = 0.001$ respectively), for $F \rightarrow L$ there are significant differences only to the last three conditions ($p = 0.01$, $p = 0.001$, $p = 0.04$ respectively). Concerning the force, we measured significant differences between conditions ending with L and the other conditions. Error on reference position reported similar behavior; moreover, we found statistical differences between $F \rightarrow R$ and the experimental modes ending with F ($p = 0.01$ for both of them). Regarding the smoothness of the movement, we found sta-

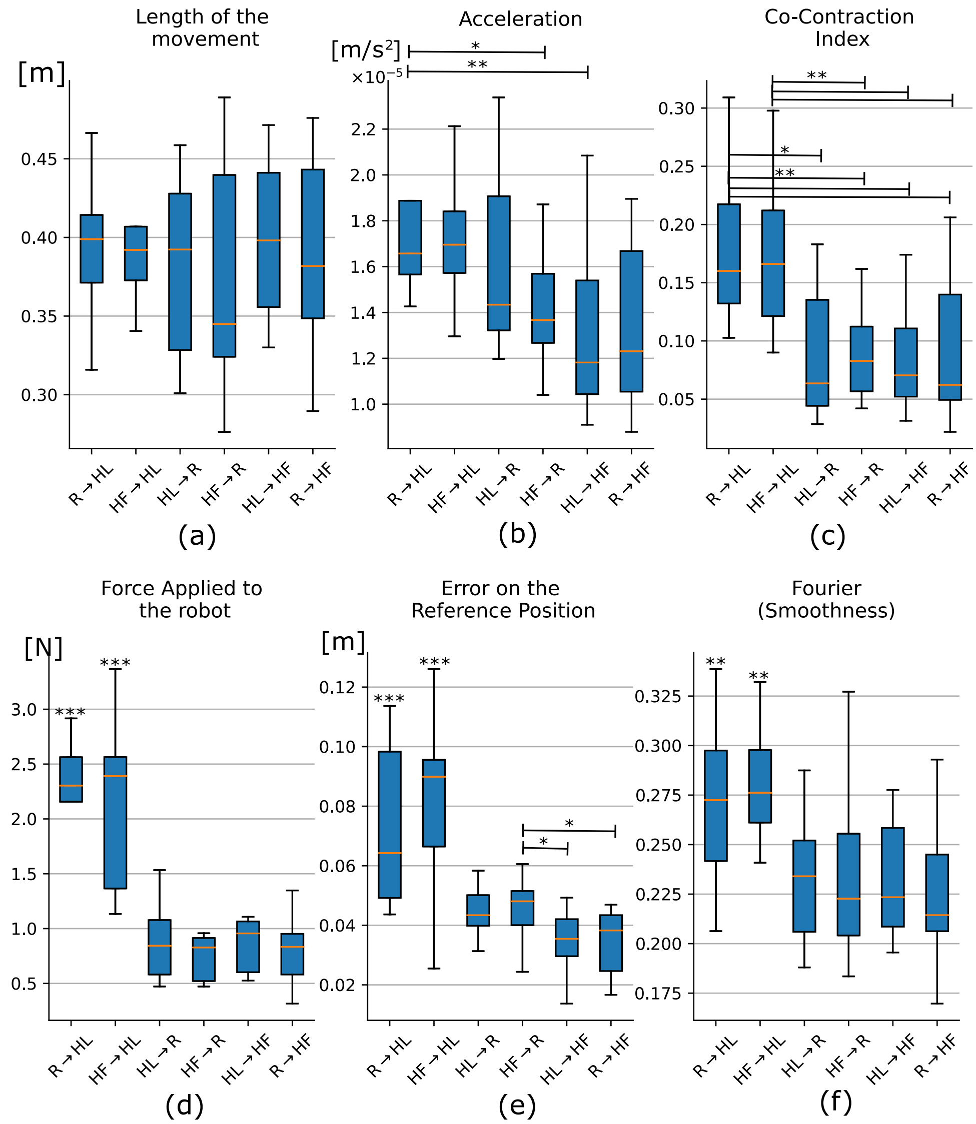

Fig. 3 Comparison of the experimental conditions at Steady State: to identify steady-state linear regressions were calculated for each of the six experimental conditions iteratively for the last 60, 59, 58 trials and so forth until the slopes were not significantly different from zero (i.e. the 95 % intervals did include zero). Stars above the boxplots indicate a statistically significant difference between conditions

tistical differences only between the first two conditions and the last four.

In summary, we can observe that certain transitions influence collaboration even at a steady state.

Modes evaluation

Figure 4 displays the distribution of the metrics described in "Performance metrics" section for the three control modes after reaching steady state. The ANOVA revealed a significant effect co-contraction index ($p < 0.001$), force ($p < 0.001$), error on the reference position ($p < 0.001$), and smoothness ($p < 0.001$). For these cases, we executed Post-hoc test. For the co-contraction index, we notice significant differences between L and R ($p = 0.001$) and between L and F ($p < 0.001$). For the force, there are significant differences between L and R ($p < 0.001$) and between L and R ($p < 0.001$). Concerning the error on the reference position, there are significant differences between L and R ($p < 0.001$), between L and F ($p < 0.001$) and between R and F ($p = 0.001$). Also the Fourier showed differences between L and R ($p < 0.001$) and between L and F ($p = 0.002$). At steady state, we notice more statistical differences between L and R than between F and R. This may suggest that participants, at steady state, tend to follow the movement of the cobot and supervise the movement. The only statistical difference between R and F is for the error on the reference position.

Regarding the number of iterations necessary for subjects to adapt, we observed that L mode generally converges faster to steady state (it takes around 12 iterations to converge) while R takes 20 iterations and F is generally slower (around 25 iterations) (Table 2).

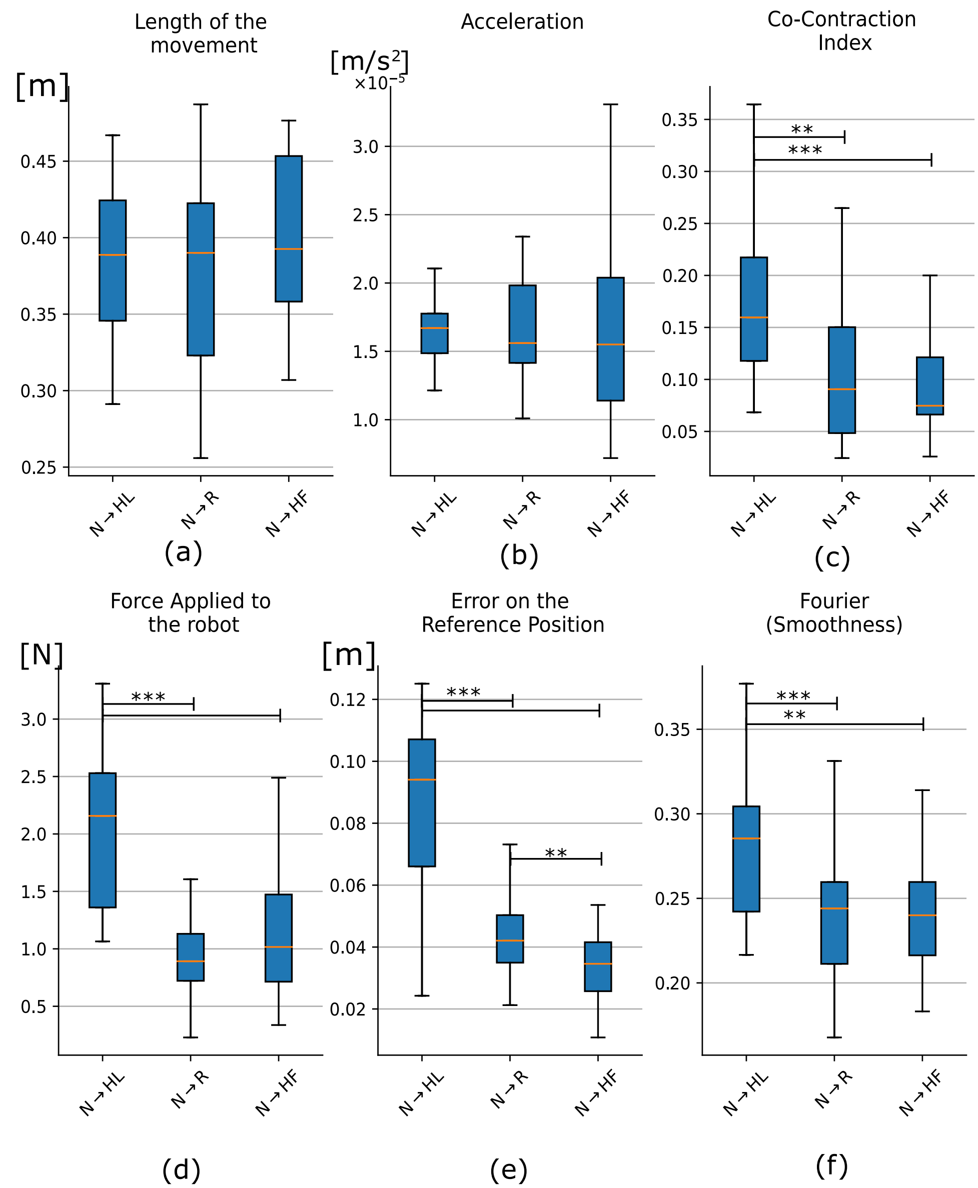

Fig. 4 Comparison of the control modes at steady state: to compare the control modes fairly and without them being affected by the transitions, we compared the scores before the transitions occurred. Stars above the boxplots indicate a statistically significant difference between conditions

Table 2 Linear regressions between the trial number and these dependent measures to identify when participants reached steady state performance

R→HL	HF→HL	HL→R	HF→R	HL→HF	R→HF	HL	R	HF
7	10	13	10	14	17	**12**	20	25

Regressions were calculated for each of the six experimental conditions and the modes, iteratively for the last 60, 59, 58 trials and so forth until the slopes were not significantly different from zero (i.e. the 95 % intervals did include zero, the first appearance of $p > 0.05$)

Questionnaire

Figure 5 displays the distribution of the scores for the questionnaire about the transitions. The Friedman tests revealed a significant effect of the *condition* factor for question Q1 (*Transition between the modes was challenging*) ($\chi^2(3) = 26.6$, $p < 0.001$) and for Q2 (*Collaboration improved after the transition*) ($\chi^2(3) = 25.7$, $p < 0.001$). For Q1, post-hoc tests indicated a significant difference between $F \rightarrow L$ and $L \rightarrow R$ ($p = 0.045$), $L \rightarrow R$ and $F \rightarrow R$ ($p = 0.003$), $L \rightarrow R$ and $R \rightarrow F$ ($p = 0.005$), $F \rightarrow R$ and $L \rightarrow F$ ($p = 0.03$) and a close difference between $L \rightarrow F$ and $R \rightarrow F$ ($p = 0.052$), while the other comparisons did not reach significance. For Q2, post-hoc tests indicated a significant difference between $R \rightarrow L$ and $L \rightarrow R$ ($p = 0.01$), $F \rightarrow L$ and $L \rightarrow R$ ($p = 0.001$), $F \rightarrow L$ and $L \rightarrow F$ ($p = 0.01$), $L \rightarrow R$ and $R \rightarrow F$ ($p = 0.045$), and close to be different between $R \rightarrow L$ and

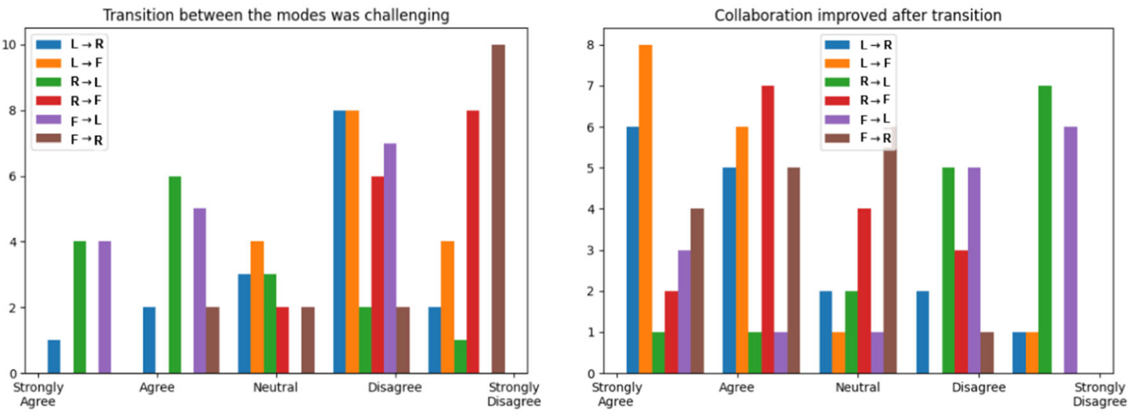

Fig. 5 Subjective questions about the transition

$L \rightarrow F$ ($p = 0.07$), while the other comparisons did not reach significance.

Figure 6 displays the distribution of the scores for the questionnaire about the three modes. The Friedman tests revealed a significant effect of the *condition* factor for question Q1 (*The mode was engaging*) ($\chi^2(3) = 8.4$, $p = 0.01$), for Q2 (*The mode was demanding*) ($\chi^2(3) = 28.6$, $p < 0.001$), for Q3 (*The mode required high cognitive effort*) ($\chi^2(3) = 13.6$, $p = 0.001$), for Q4 (*The mode required high physical effort*) ($\chi^2(3) = 29.1$, $p < 0.001$) and for Q5 (*The mode was boring*) ($\chi^2(3) = 12.16$, $p = 0.002$). For Q1, post-hoc tests indicated a significant difference between R and F ($p = 0.02$). For Q2, post-hoc tests indicated a significant difference between L and R ($p = 0.003$) and L and F ($p = 0.001$). For Q3, post-hoc tests indicated a significant difference between R and F ($p = 0.04$) and L and F ($p = 0.02$). For Q4, post-hoc tests indicated a significant difference between L and the other two conditions($p = 0.004$, $p = 0.001$ respectively). For Q5, post-hoc tests indicated a significant difference between R and L ($p = 0.007$). All the other comparisons did not reach significance.

Discussion

This section discussed the main results in terms of transitions between modes and modes individually, both in terms of objective metrics and questionnaires. Finally, we discuss some of the possible limitations of the existing study.

Transitions

Figure 2 reports on the performances we chose to evaluate (length of the movement, acceleration, co-contraction index, force, error, and smoothness) at the first iterations after switching between one mode to another. We observe statistical differences in movement length only between the second ($F \rightarrow L$) and the fifth experimental condition ($L \rightarrow F$). Although there are no statistical differences, we observe a lower median for both the first ($R \rightarrow L$) and fourth transitions ($F \rightarrow R$). Similar considerations apply to the error on the reference position (statistical differences for $R \rightarrow L$, $F \rightarrow L$ and $F \rightarrow R$). These results suggest that for these three experimental modes, the quality of motion is affected by the transition losing the ability to follow the reference. We think this is because the participants are accustomed to greater robot autonomy, and when this fails, they do not take over quickly enough to take the lead.

We also observed an interesting effect regarding co-contraction and applied force. The co-contraction index of the third experimental condition ($L \rightarrow R$) is similar to that of the first two conditions ($R \rightarrow L$ and $F \rightarrow L$), despite not showing statistical differences from the last three (as the first two do). The applied force, on the other hand, shows how both the third and fourth conditions ($L \rightarrow R$ and $F \rightarrow R$ respectively) show differences from the last two, and the fourth has a higher median. These results suggest that the operator applies a different force profile dependent on what the transition was. This type of behavior may be due to a stiffening of the operator (and thus an increase in ICC without a consequent increase in the force applied on the cobot) in the transition phase. We think this may be due to either a desire to maintain stability in the movement or an attempt to better understand the type of interaction being performed with the cobot.

Figure 5 showed how the subjects perceived the transitions. Subjective questionnaires showed that the subjects found challenging to pass to F modes (Fig. 5a) and, on the contrary, they showed that the simplest transition is $L \rightarrow R$. Collaboration perception is improved in the cases where previously the human is the leader (Fig. 5b) while it remains more or less constant in the switching from human leader to reciprocal, conversely, it is worsened when the human is the leader after the transition. Similar behavior has been

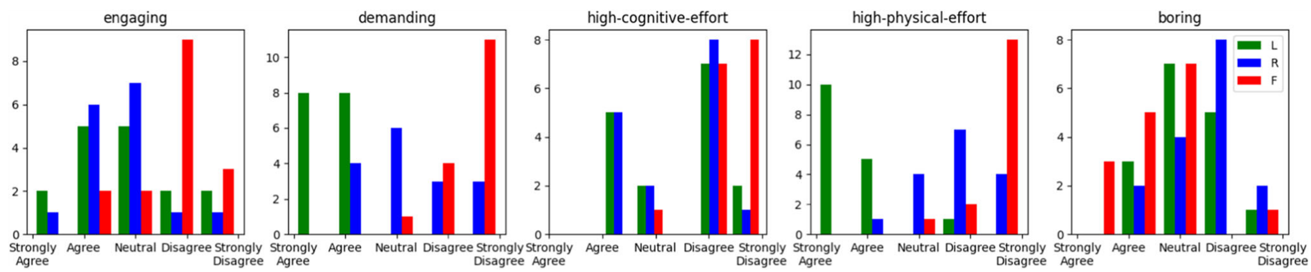

Fig. 6 Subjective questions about the three modes: Human Leader (L), Human Follower (F) and Reciprocal (R)

observed previously in movement length. This indicator reinforces our hypothesis that subjects have difficulty taking over abruptly when the cobot's cooperation fails. Similar undesirable behavior can also be imagined in the case of two human subjects in which one of the two participants stops making a contribution to the collaboration. Undoubtedly, such conduct would be misinterpreted by the second participant. Indeed, it is well known that, in general, people tend to appreciate more those who evolve their behavior from negative to positive while they appreciate less those who change from a perceived positive behavior to a negative one. In the literature, this effect is called the "gain-loss effect" (Aronson & Linder, 1965), and it has been shown that it can also be applied to interaction with robots (Nakamura & Umemuro, 2022). So, to answer (**Th1:** *How the switching between modes is perceived by the human? Is the performance influenced in the first iterations of the task after the switching?*), we can state that indeed the transition influences movement performance in the early stages and that the quality of the movement depends on how it was previously performed. As for (**Th3:** *Do humans prefer some transitions with respect to others?*), however, we can say that subjects prefer to abandon the human leader mode and prefer to either follow the robot or to collaborate (reciprocal).

Figure 3 reports on the performance metrics after the steady state is reached. We expected that at steady state, the impact of switching had now been nullified, and instead, some results suggest that operator performance is still affected. Indeed, although we observed no statistical differences in movement length, there is a lower median for both the fourth transitions. Similar considerations apply to the error on the reference position (statistical differences for the first two and the fourth). Interestingly, the movement length for the human leader cases is about the same as for the other cases while the error is very different. Our intuition is that this might be due to the fact that the human imposes a different trajectory than the cobot but is still functional for task execution. These results refer to (**Th2:** *Does a past transition influence the collaboration after the steady state is reached?*), suggesting that the performance of the collaboration is also influenced after the steady state is reached.

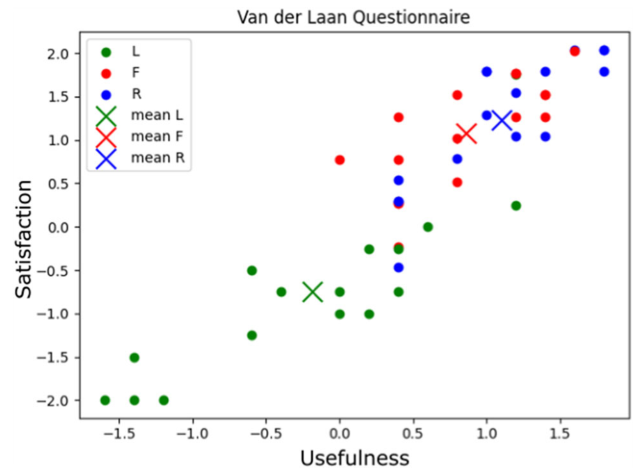

Fig. 7 Results of the Van der Laan questionnaire. This scale assesses system acceptance on two dimensions: a Usefulness scale and a Satisfying scale

Modes

Figure 4 reports on the performance metrics for the three control modes observed separately after the steady state is reached. We can observe that there were no statistical differences in movement length, so movement performance was therefore not affected by mode choice. On the other hand, if we look at the distance to the reference trajectory, we notice statistically significant differences that allow us to say that in the three cases, the human–robot pair performed three different trajectories. Looking at the other graphs (ICC, force, and smoothness), we observe statistical differences only between L and the other two modes. These results suggest that the R mode does not significantly affect the operator's effort and smoothness of the motion while allowing the operator to impose his own trajectory, as observed in the error from the reference. This happens because of the way R was constructed, in fact, whenever the subject decides to change the trajectory from that imposed by the cobot the subject increases its stiffness inducing the cobot to become compliant.

In Fig. 6 we make the following observations: the subjects perceive the R and the F modes as engaging, the F is not demanding while the L is highly demanding also from a cognitive point of view and from a physical point of view, the R mode is arranged in the middle of these two extremes, subjects perceive the R mode as less boring with respect to the other modes. In a similar way, Fig. 7 displays the three modes on the Van der Laan scale assigning both a score of satisfaction and of use-fullness. We observe that the mean value of the R and of the F mode are very close to each other, and at the same time, they are distant from the mean of the L modes. In accordance with this scale, there is a small benefit in the R with respect to using F mode. Thus, answering question **Th5** (*For this specific task, does human prefer one mode with respect to another?*), we could state that subjects much prefer to collaborate with a cobot in R and L modes than a cobot in F mode. At the same time, we note a slight preference toward the R mode. Talking with participants, we got the idea that subjects preferred approaches in which the cobot was active because they were less strenuous. At the same time, we think R mode was better perceived by subjects because they felt they had more control over the task. Moreover, we think R is more convenient because it is less boring, more engaging (with respect to F mode), and requires less effort (with respect to L mode). For this reason, we think it is better suited for tasks in which it is important to be engaging (for instance, when human and robot executes dangerous movements).

The performed statistical analyses ("Statistical analysis" section) show how the general human subject finds equilibrium in its behavior (and thus scores settle) faster in the human leader case. In contrast, the human follower is, in general, slower to converge to an equilibrium solution. The reciprocal mode condition generally requires intermediate times. Thus, answering question **Th4** (*Does human adapt faster to some modes with respect to others?*), we could state that human subjects adapt to the cobot's control modes at different times and that the greater the participant's autonomy, the shorter the time. This result is probably due to the fact that subjects search harder for solutions that limit the amount of fatigue in performing the movement. Furthermore, it has been shown that humans, in general, have a greater ability to adapt to tasks than the robot (Fitts, 1951), we think that in the L case, the subject has full decision-making power and thus is not somehow slowed down by the cobot's reduced capabilities as is the case in the R and F cases.

Limitations

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 that may have different attitudes when interacting with a cobot (Maurice et al., 2018). Second, the planar sawing task was simple and common. In this sense, we do not know if our results can be generalized to other tasks involving large and heavy loads with movements on the three dimensions, a situation that is often found in manufacturing where robots physically assist workers [e.g., manipulating car parts as in Maurice et al. (2019)]. In any case, the results we obtained allow us to demonstrate how important the type of training the operator must undergo is and how important it is to manage the robot controller transitions in a consonant manner.

Conclusion

In this paper, we studied how humans adapt in a collaborative sawing task when cobot suddenly changes the control strategy. The results suggest that in this kind of task, not only the type of the current role of the cobot, but also the past ones influence the behavior of the human operator. In our specific task, the results seem to indicate that: transition influences movement performance in the early stages (**Th1**) and at steady state (**Th2**), subjects prefer to abandon the human leader mode and prefer to adopt modes in which there is either reciprocal mode or follower mode (**Th3**), they adapt faster to leader mode (**Th4**), subjects prefer recirocal mode (**Th5**).

Our work points out how important it is to consider the adaptive process in many environments where humans and robots physically interact: industry, home automation, and rehabilitation. In future work, we would like to test the adaptation of the human on different types of tasks to see if the results are consistent with what we have seen for collaborative sawing. Also, we would like to use the collected data to build a model of how a human adapts to a robot. We think this model could provide us with an indispensable tool for collaboration. Indeed, if the robot could predict how a subject adapts to a given policy it could vary its policy with the intent of accelerating the adaptation (in case the equilibrium condition was good) or on the contrary guide it to another equilibrium condition. These kinds of strategies are already present in the literature (Nikolaidis et al., 2017), but to the best of our knowledge, there are few cases where they are used in pHRI.

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Declarations

Conflict of interest The authors declare no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the TU-Delft's ethical committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent All the participants involved in the experiments signed an informed consent form to participate in the study.

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