This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Human Adaptation to Human–Robot Shared Control

Negin Amirshirzad, Asiye Kumru, and Erhan Oztop, *Member, IEEE*

***Abstract*—Human-in-the-loop robot control systems naturally provide the means for synergistic human–robot collaboration through control sharing. The expectation in such a system is that the strengths of each partner are combined to achieve a task performance higher than that can be achieved by the individual partners alone. However, there is no general established rule to ensure a synergistic partnership. In particular, it is not well studied how humans adapt to a nonstationary robot partner whose behavior may change in response to human actions. If the human is not given the choice to turn on or off the control sharing, the robot–human system can even be unstable depending on how the shared control is implemented. In this paper, we instantiate a human–robot shared control system with the "ball balancing task," where a ball must be brought to a desired position on a tray held by the robot partner. The experimental setup is used to assess the effectiveness of the system and to find out the differences in human sensorimotor learning when the robot is a control sharing partner, as opposed to being a passive teleoperated robot. The results of the four-day 20-subject experiments conducted show that 1) after a short human learning phase, task execution performance is significantly improved when both human and robot are in charge. Moreover, 2) even though the subjects are not instructed about the role of the robot, they do learn faster despite the nonstationary behavior of the robot caused by the goal estimation mechanism built in.**

***Index Terms*—Human–robot interaction, motor skill acquisition, sensorimotor learning, shared control.**

I. Introduction

THERE is a huge potential for humans and robots to synergistically work together to achieve high performance in a vast array of tasks. Classically, robots have been viewed as devices that perform physical tasks on command with human supervision. This, however, has changed; robots are now envisioned as capable *partners* that are expected to cooperate with humans intuitively. For some domains humans are still superior to robots, where robust perception and decision making with partial information, flexibility and dexterity are needed; on the other hand, robots are resistant to hazards, robust to fatigue, and good at precise low-level motion planning and repetitive tasks.

Manuscript received August 18, 2017; revised January 30, 2018 and August 31, 2018; accepted November 17, 2018. This work was supported by the European Community's Seventh Framework Programme FP7/2007-2013 under the Grant agreement 321700, Converge. This paper was recommended by Associate Editor Rene van Paassen. *(Corresponding author: Negin Amirshirzad.)*

N. Amirshirzad is with the Ozyegin University, Istanbul 34794, Turkey (e-mail: negin.amirshirzad@ozu.edu.tr).

A. Kumru is with the Department of Psychology, Ozyegin University, Istanbul 34794, Turkey (e-mail: asiye.kumru@ozyegin.edu.tr).

E. Oztop is with the Department of Computer Science, Ozyegin University, Istanbul 34794, Turkey (e-mail: erhan.oztop@ozyegin.edu.tr).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/THMS.2018.2884719

Therefore, combining human and robot skills via intelligent interfaces seems very appealing. In this direction, establishing principled shared control methods to seamlessly blend the control between the human and the robot to enable the combined system to surpass both the robot and human performance with reduced human effort is a prime goal for robotics.

One way the robots and humans can be put in cooperation is via human-in-the-loop systems, in which the human and the control system are both given control over the robot with some arbitration or control blending mechanism (e.g., [1]–[4]). In such a system, ideally both systems must adapt to ensure high task execution performance and natural interaction for the human [5]. For example, in the case of selfdriving, vehicles can monitor and learn from the driver's habits so as to adopt an optimal control arbitration [6], [7]. In the case of exoskeleton systems, the system may monitor and provide assistance according to the state of the user and the overall task execution performance [8]. In such systems, robot adaptability is critical not only for compensating for individual differences but also for providing online adjustments in response to changes in human behavior during shared control. The work in [5] addresses human policy differences explicitly and adapt the robot policy for improved task performance without sacrificing from human trust. This is achieved by obtaining an estimate of the human adaptability level, after which the robot decides whether it would comply with the human strategy (for a nonadaptable partner) or guides the (adaptable) human partner to a better strategy.

The completion of certain tasks can only be specified with respect to a set of task parameters, such as the goal position for a reaching task. In such cases, for effective and natural task execution, besides task knowledge, the robot must have some mechanism to infer the goal of the human partner [3], [9]. In most studies, the goal is known to the robot or explicitly given, which may be an unrealistic assumption, or may hamper natural collaboration (see [3] and citations therein).

Although it is known that human adaptation does happen in human–robot shared control systems [5], there are virtually no studies that explore the human adaptation in shared control systems in a systematic way. With this study, we aim to make a contribution in this direction by assessing the differences between human adaption in human teleoperation (no-shared control) versus human shared control, where the human and the robot act together to perform the given task.

A simple way of having a human interact with a robot is so called direct control [10]–[12], where the human controls the robot by physically holding and moving it through desired postures. At the basic level, direct control is limited to teaching a robot position control-based tasks [13]. It can be however, cast in to a physical robot–human shared control system by adopting a robot policy that facilitates modification through physical guidance from the human [14]. In the human-in-the-loop control systems, we consider [1], [13], [15], [16], critically, the human is placed in the control loop, and takes share in control in real-time to make the robot perform a given task; as such, physical contact with the robot is not a prerequisite. This paradigm has been successfully used to obtain robot skills, such as ball manipulation [13] with a five-fingered robotic hand, balanced inverse kinematics on a humanoid robot [15], and tasks involving force-based policies [15], [16]. In these studies, human-in-the-loop control framework was used to obtain an autonomous controller for the robot and aimed at eventually removing the human from the control loop. However, in assisted and shared control, both parties are envisioned to stay engaged in the task. For the former, the robot takes share in control and helps the human accomplish the desired task by making it easier and more seamless [2], [3], whereas in the latter a synergistic coupled system is formed by the human and the robot to perform the desired task [4].

The current study addresses the latter, i.e., it focuses on the questions of whether effective shared control is possible without explicit shared goal specification (communication) and investigates how the human partners adapt. It is known that humans and robots should have a common goal to work cooperatively [17]; thus, goal inference becomes critical when no communication is allowed. In general, effective collaboration requires coordination and the ability of partners to infer each other's intentions [18], [19]. In many cases, coordination error and miscommunication between the human and autonomous agent will result in system failure [20]–[22]. Hence, ensuring the ability to anticipate the needs and goals of each other from behavior during collaborative work is critical to achieve good team performance [5], [23]. It is not uncommon in human–robot interaction and assistive teleoperation studies that the robot is assumed to know the human intention [24]–[32]. In some other studies, it is assumed that the human is following one of a predefined goals or paths, and then a classifier is used to decide the human goal [33]–[39]. In many real-world scenarios, explicit goal specification may not be possible, or is undesirable [3]. Furthermore, discrete set of goals may be restrictive for some task domains. In the current study, to be more general, the robot goal estimation does not assume a discrete set of goals. In a recent report [2], [3], "policy blending" is proposed to address shared control in scenarios where the arbitration of the control policies of the human and robot must be undertaken based on robot's prediction of the user intent. In [2], [3], a general, principled intention understanding mechanism is used, and it is shown that the overall system is effective in extending the range of human movements in assistive reach-to-grasp tasks. In this work, on the other hand, we adopt a simple task-specific intention prediction mechanism but use a task with nonnegligible dynamics to show how synergistic shared control can be achieved with it, and how human sensorimotor system adapts to a nonstationary robot partner. In particular, we explore if there is any long-term advantage in task performance when humans share control with a machine—that makes the task harder at first—and how they progress and adapt to the system. The results indicate that indeed humans quickly learn to adapt to a robot partner who has nontrivial adaptive behavior and exploit it for higher task performance. Furthermore, with this strategy, effective human learning rate is increased and thus the time needed to reach a given performance level is reduced.

II. Methods

A. Shared Control Framework

We base our shared control framework on the human-in-the-loop control approach as in [1], [13], [16]; but the aim is collaborative task execution performance improvement rather than autonomous robot skill generation. In this framework, the robot shares the control with the human to accomplish a given task by inferring the human intention. In a given task, the intention is usually modeled as a goal specifying parameter, e.g., target of reaching. When the robot estimates the human goal correctly and has a control policy compatible with the human partner, then the system effectively becomes assistive. In the current setting, we assume no direct communication between the robot and the human so that both parties do not know for sure the goal of their partner. During the human execution of the task through the robot, the robot system simultaneously estimates the human goal, and based on its estimate, takes share in control. In general, control sharing can be implemented in several ways, such as responsibility arbitration or a weighted summation of human and robot commands. In the current report, as in [3], we take a convex combination of the commands generated by the two parties to determine the net motor command (desired angle changes) sent to the robot (1).

$$\mathbf{c_{net}} = \omega \mathbf{c_H} + (1 - \omega)\, \mathbf{c_R} \tag{1}$$

where ω is a weight parameter between 0 and 1; $\mathbf{c_H}$ is the human command, $\mathbf{c_R}$ is the robot command. The general framework is illustrated with Fig. 1, where the plus sign in the control sharing is used figuratively and indicates convex combination in this report.

B. Designed Task

We have realized the shared control framework depicted in Fig. 1 with the "ball balancing task" with a robotic arm as the partner, which holds a tray containing a free rolling ball (3 cm in radius, Styrofoam ball covered with reflective tape). The goal of the task is to bring the ball to a desired target position (the goal) by tilting the tray using two axes. The ball must reach the goal and stay there still for 2 s for task completion. In the conducted experiments, the desired target position is marked on the tray for the human operator. However, the robot is not given this information; further it has no knowledge that a fixed discrete set of targets were used. Thus, the goal inference needs to produce continuous goal position estimates on the tray. The human control of the robot is achieved through a straightforward teleoperation setup, where the operator controls the two degrees-

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

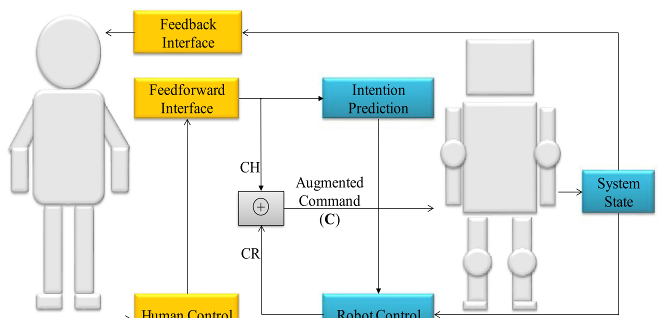

Fig. 1. In this framework, the human operator controls the robot in real-time to make it achieve a given task that may have a set of task parameters (e.g., target position). Simultaneously, the robot tries to infer the human intention, i.e., task parameters reflecting the human intention and generates commands based on its inference. The two control outputs are then integrated and sent to the plant for shared control. The feedforward interface maps human movements to robot commands, whereas the feedback interface can be identity (i.e., human directly observes the robot) or a system that uses robot state information to generate sensory stimuli for the human partner.

of-freedom of the robotic arm by using a standard computer mouse. The human and system generated motor commands are combined with equal weight $(\omega = 0.5)$ in (1).

C. Robotic Setup

We used an anthropomorphic robotic arm (6DOF Kuka Agilus R6000) to hold the tray and act as the partner for the ball balancing task. A tray of 70 cm by 70 cm square was attached to the end effector of the robotic arm. The perimeter of the tray was surrounded by walls to keep the ball falling over. The robot configuration was chosen such that two wrist joints of the robotic arm could be used to tilt the tray in the global pitch and roll axis. An infrared camera system (OptiTrack) was mounted above the robotic arm to capture and track the position and velocity of the ball in real-time with a frequency of 250 Hz. The edges and the center of the tray were detected by the camera and scaled to the real dimensions of the tray in order to obtain the position of the ball on the tray in metric units.

1) Robot Teleoperation: To teleoperate the Robotic arm, a standard computer mouse is used. The human movements, i.e., the horizontal and vertical displacements of the mouse are linearly scaled and sent as the desired angular changes of the robot joints, which are fulfilled by the low-level motor control loop of the Kuka R6000 system, creating roll and pitch movements of the tray inducing ball motion. The robot angles were commanded at approximately 250 Hz with (2) and (3).

$$\theta_{\mathrm{pitch-desired}} = \theta_{\mathrm{pitch}} + \Delta\theta_{\mathrm{pitch}} \tag{2}$$

$$\theta_{\mathrm{roll-desired}} = \theta_{\mathrm{roll}} + \Delta\theta_{\mathrm{roll}} \tag{3}$$

where θ_{pitch} and θ_{roll} denote the joint angles of the robot (see Fig. 2), $\Delta\theta_{\mathrm{pitch}}$ and $\Delta\theta_{\mathrm{roll}}$ are the components of the human command $\mathbf{c_H}$ obtained based on the horizontal (Δd) and vertical (Δh) displacements of the mouse as given in (4). In (4), k is a positive scaling coefficient chosen experimentally for providing

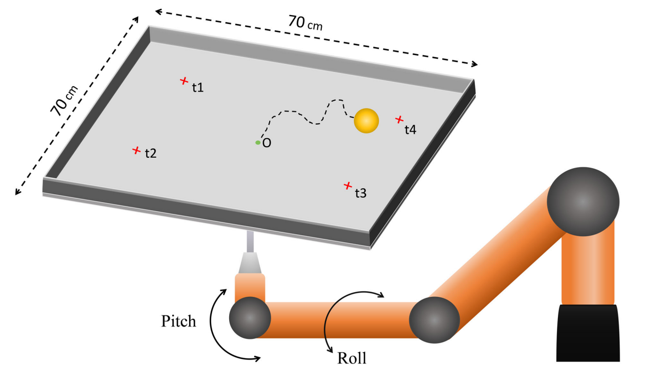

Fig. 2. Task setup is illustrated. Only the indicated axes of the robot are used to induce roll and pitch movements of the tray. The tray dimensions are 70 cm by 70 cm and the ball radius is 3 cm. Considering O (0, 0) as the center of the tray, the target positions are t1(20 cm, 20 cm), t2(−20 cm, 20 cm), t3(−20 cm, −20 cm), and t4(20 cm, −20 cm).

an intuitive teleoperation within the velocity and torque limits of the robot system (in the experiments reported $k = 1$).

$$\mathbf{c_H} = [\Delta\theta_{\mathrm{pitch}}, \Delta\theta_{\mathrm{roll}}] = k\,[\Delta h, \Delta d]\,. \tag{4}$$

2) Shared Robot Control: When the shared control is on, the human operator and the robot system generate motor commands that are combined to produce the net motor command [$\mathbf{c_{net}}$, as given in (1)]. The human is told the goal position; however, the robot has no knowledge of the goal and needs to infer this by observing human control commands and/or ball positions. Once the robot has an estimate of the human goal (which can be any continuous position value on the tray), the robot generates motor commands to bring the ball to the estimated goal. In this report, we assume that the robot has a basic control policy to perform the task given a target location. We obtain this basic policy through learning by demonstration as described next.

a) Autonomous Controller: We equip the robot with the basic skill of ball balancing via learning by demonstration approach (e.g., [13]). For this an expert robot operator performs a series of ball balancing demonstrations, while the robot and ball related data together with the human commands are collected to synthesize an autonomous controller. The goal of the controller is to generate appropriate robot commands to bring the ball to the desired position on the tray given the state of the system. The state of the system is parameterized with the goal position and is a time varying vector as defined in (5).

$$\mathbf{s}_{\mu_{\boldsymbol{x}},\mu_{\boldsymbol{y}}}(t) = \begin{matrix} [x(t) - \mu_x, y(t) - \mu_y,\ \dot{x}(t), \dot{y}(t), \\ \theta_{\mathrm{pitch}}(t),\ \theta_{\mathrm{roll}}(t),\ \dot{\theta}_{\mathrm{pitch}}(t), \dot{\theta}_{\mathrm{roll}}(t)] \end{matrix} \tag{5}$$

where $(x,\ y)$ and $(\theta_{\mathrm{pitch}}, \theta_{\mathrm{roll}})$ denote the ball position and the joint angles of the robot, (μ_x, μ_y) is the goal position on the tray (i.e., the position that the ball must be brought), and $(\dot{\cdot})$ indicates time derivative. During human demonstrations, for each data sampling period, human generated commands and corresponding state vectors are recorded. This allows us to con-

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

struct a state matrix $\mathbf{S}$ where each row is a state vector at some time instant [as in (5)] and a command matrix $\mathbf{C}$ where each row is a human command [as in (4)] issued for the corresponding row in $\mathbf{S}$. Thus, the number of rows in $\mathbf{S}$ and $\mathbf{C}$ depends on the sampling period, the number of demonstrations and their durations. If $\mathbf{S}$ and $\mathbf{C}$ capture an expert human response for a wide range of the states of the system, it is a rather trivial machine learning task to build a controller or robot policy that will mimic human control. In this work, by assuming approximately linear relation between the control commands and the system state, we obtain the weight matrix $\mathbf{W}$, which maps the states to the corresponding commands with (6).

$$\mathbf{W} = \mathbf{S}^{\dagger}\ \mathbf{C} \tag{6}$$

where $\mathbf{S}^{\dagger}$ is the pseudoinverse of $\mathbf{S}$. With $\mathbf{W}$, the robot can generate commands ($\mathbf{c_R}$) to bring the ball to a desired location (μ_x, μ_y) by using (7), where the current state ($\mathbf{s}_{\mu_{\boldsymbol{x}},\mu_{\boldsymbol{y}}}$) is defined with respect to a desired location as in (5). Note that state $\mathbf{s}_{\mu_{\boldsymbol{x}},\mu_{\boldsymbol{y}}}$ is a time and goal dependent vector; thus (7) defines an autonomous control policy whose parameters are specified solely by $\mathbf{W}$ and μ_x, μ_y. In this sense, the control policy can be considered as a feedback control policy since state $\mathbf{s}_{\mu_{\boldsymbol{x}},\mu_{\boldsymbol{y}}}$ includes the positional error terms $x(t) - \mu_x, y(t) - \mu_y$ as its components [see (5)].

$$\mathbf{c_R} = [\Delta\theta_{\text{pitch}}, \Delta\theta_{\text{roll}}] = \mathbf{s}_{\mu_{\boldsymbol{x}},\mu_{\boldsymbol{y}}}\ \mathbf{W}. \tag{7}$$

To obtain an autonomous policy for our robot, we collected 200 s of expert demonstration with random starting ball positions and tray center as the target, and applied linear regression as explained above. The root mean square error, RMSE[1] for the fits were 0.17° and 0.27° for each joint angle. Trials with this controller could balance the ball in potential desired target locations within an acceptable accuracy (i.e., within 3 cm off the target, which is the radius of the ball used in the experiment). We did not further try to improve the robot performance (e.g., by collecting additional data from expert demonstration) as we wished to see how human and an imperfect robot can form a synergistic well performing system. However, in an earlier preliminary study we have compared the autonomous task execution performance of this controller with that of humans by using a small subject group and found that the robot can perform the task autonomously and can do it faster than the humans on the average, but with less accuracy [4].

It is worth underlining that in both human control (nonshared teleoperation) and shared control conditions, the low-level controller that comes with the robot is on, which involves high control rate feedback loop for accurate joint angle tracking. This low-level control makes the robot follow human generated commands in the human control condition, and combined human and autonomous controller commands in the shared control condition. Thus, in this study the robot was never engaged fully autonomously, either it was teleoperated by the human operator or commanded by the combined human and autonomous control output.

b) Human Intention Inference: In the ball balancing task, human intention refers to the goal position that the human is asked to bring the ball to. This information and its discrete nature are unknown to the robot. The task of intention inference is to estimate a continuous position on the tray. For this, a straightforward algorithm is implemented. The robot monitors the ball positions in a 4-s sliding window, and by using the data points collected in the window estimates the goal of the human operator. In this study, we did not systematically analyze the effect of the window size to keep the experiment size tractable, but instead determine it empirically by considering tray dimensions and typical ball velocities experienced. The exact effect of this parameter is left for a future focused experiment. The ball position is assumed to have a normal distribution (8).

$$P(x, y) \sim N\ (\mu\ ,\ \mathbf{\Sigma}) \tag{8}$$

where x and y indicate the ball positions in two axes of the tray. During human operation, the mean vector μ and covariance matrix $\mathbf{\Sigma}$ are found in real-time. The mean vector μ is taken as the robot estimation of the intended target position of the human and is used in (5) and (7) to generate the robot commands for bringing the ball to the estimated target once the first four seconds has elapsed. Thereafter, this estimation is continuously updated during the task execution. The covariance matrix is not used in the experiments reported in this article but can be used as an indicator for the confidence of the estimate.

D. Experiments

Although we may hope that a robotic system as described above with a potential to assist a human partner would lead to high task execution, a human may find it easier to use the robot as a passive tool (i.e., teleoperate the robot) to perform the task. So, is the system we outlined any better than simple teleoperation? To be more concrete, is the combined task performance elevated, and/or the human effort is reduced in the shared control condition? To answer these questions, we designed and ran a set of experiments under two conditions and compared their performances: First, *human control condition*, where the human performed the task through teleoperation of the robot and second, *Shared Control condition*, where the human shared control with the robot, and thus potentially could receive support from the robot system to complete the task. In the former, only human teleoperation commands drove the robot as explained in section “robot teleoperation.”. In the latter, both human and robot are involved in generating the control commands to accomplish the given task, as explained in section “shared robot control.” However, neither of the subject groups were informed about the nature of their experimental condition; both groups thought they would teleoperate the robot to perform the task.

1) Experiment Design: In total of 20 (12 males, 8 females) naive human subjects volunteered to participate in the experiment. They were students majoring engineering or psychology at Ozyegin University in Turkey. The number of fe-

[1]RMSE $= (\sum_{i=1}^{N} (\Delta\theta_i - \Delta\theta_i^{\text{estimated}})^2/N)^{1/2}$ where i runs over the training data points, and θ indicates either roll or pitch angle.

male and male subjects to go through human control and shared control conditions and the mean age of the subjects assigned for each condition were matched. In the human control condition, six male and four female students with the mean age of 25.80 ranging from 22 to 28 years participated. In the shared control condition, six male and four female students with the mean age of 25.90 ranging from 23 to 31 years participated. Four target positions, approximately the centers of each quadrant, were used as the potential target ball positions for the subjects; but, as far as the robot concerned, the human goal could be any position on the tray. At the beginning of each experimental trial, the ball was positioned at the center of the tray with zero velocity, and the subjects were asked to bring the ball on the marked target position and keep it there still with a maximum of 3 cm offset from the target point (since the radius of the ball used in the experiment was 3 cm). The target positions and their orders were consistent for all the subjects in both conditions. The subjects were told that the ideal trajectory was the diagonal path from center to the targets; but, they were not imposed any hard constraints or failure conditions. In the rare case of ball jumping out of the tray, the trial would be repeated. Although there were no time limit constraints, subjects tended to complete the task fast (as opposed to trying to slowly and carefully roll the ball to the target). The subjects could see the experimental setup with a direct view of the tray and the ball to complete the task.

Experimental trials were grouped into blocks (subsessions); four trials with shuffled targets made up a block. In turn, four blocks are grouped into sessions. Thus, one experimental session included 16 trials. For each subject, four experimental sessions were conducted in separate but consecutive days, making it a total of 64 trials for each subject. The purpose of this was to investigate the sensorimotor learning process taking place in the subjects over days. At the beginning of the first experimental session the instructions, including the task description, how to use the interface, when to start, and when the task finishes were given to the subjects. To not tire the subjects, after each block they were allowed to take a short break. Subjects were not told which condition (human control or shared control) they were assigned to; thus, the subjects in the shared control group did not know that the robot was also involved in the task. At the end of the last experimental session, the subjects were asked to fill a questionnaire about the experiment.

2) Performance Measure: We chose trajectory length, i.e., the length of the path the ball traveled from the beginning of the trial until the target location to measure task performance. Shorter trajectory lengths indicate skilled task executions leading to higher task performance. Another related possible task performance measure is completion time. We adopt the trajectory length as it is more robust to individual differences as wobbling around a target in a small region incurs less trajectory-cost compared to time-cost. To demonstrate the general idea of "good" and "bad" performance, two ball trajectories with their human and robot control contribution are shown in Fig. 3. In addition to our primary performance measure of trajectory length, we also investigated the compatibility of hu-

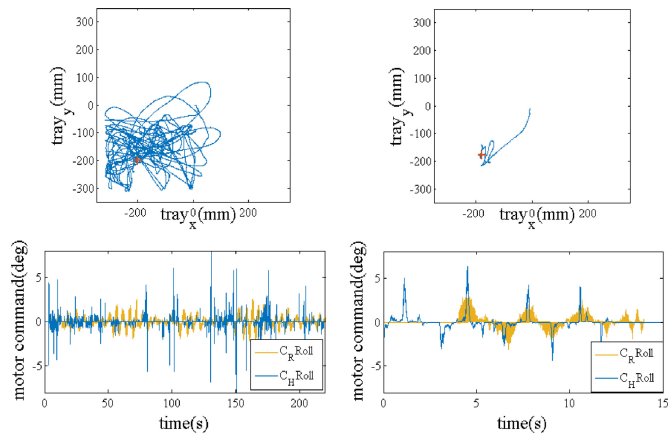

Fig. 3. Upper panel: ball position trajectory of two subjects in shared control condition to balance the ball at the lower left quadrant. Left depicts an early low performance trial, whereas right depicts a high performance trial after learning. Lower panel shows human and robot generated commands during these trials.

man and robot commands in the shared control condition by using the degree of linear correlation measured by the Pearson correlation coefficient [40] between the robot and human commands.

E. Analysis

To compare the performance of the subjects in the two conditions (shared control vs. human control) based on trajectory length we used one-way multivariate analysis of variance (MANOVA) and analysis of variance (ANOVA) [40]. MANOVA is a statistical procedure for comparing multivariate sample means when there are two or more dependent variables. The main objective in using MANOVA is to determine if the response variables (subject improvement in performing the task in our case) are altered by the experimenter's manipulation of the independent variable (human control versus shared control). Analysis of variance (ANOVA) is a statistical procedure to compare two or more means to see if there are any reliable differences among them, and thus is used to assess the progress over days for each condition. To do these analyses, first, the four trials of each block, and then, the four blocks of each day are grouped. In addition, regression analysis is applied to inspect the learning progress of the subjects over trials in both conditions.

Finally, to investigate whether the compatibility of the human and robot commands corroborate the faster learning observed in the shared control condition, we ran additional analysis for the shared control condition data. To be concrete, we examined how the linear correlation between the human and robot commands change over days. For this, first, we calculated the Pearson correlation coefficient [40] between the human and robot separately for roll and pitch commands for each trial, giving us 16 correlation value pairs for each day. Then, over the possible pairs of days we ran repeated measures ANOVA with a Greenhouse-Geisser correction (as our data violated the assump-

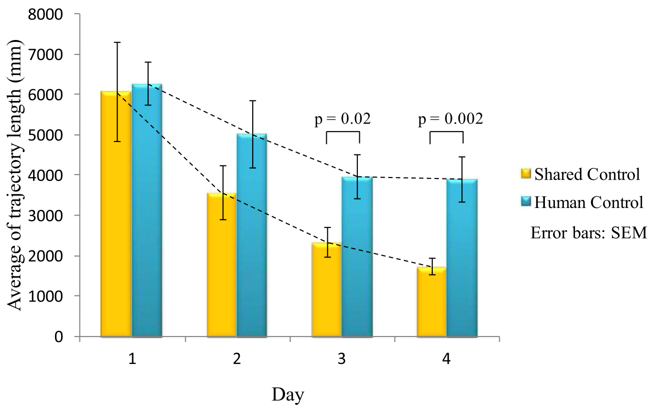

Fig. 4. Means for day 1, day 2, day 3, and day 4 performance of human control and shared control conditions. $p \leq 0.05$ indicates significant difference. Error bars over the means indicates standard error of the mean (SEM).

TABLE I
MEANS, STANDARD DEVIATIONS, AND MANOVA FOR BLOCK1, BLOCK 2, BLOCK 3, AND BLOCK 4 PERFORMANCE OF HUMAN CONTROL AND SHARED CONTROL FOR THE DAY 1

Blocks	Condition	Mean(mm)	Std. dev(mm)	ANOVA
block 1	Shared control Human control	9707.7720 8280.4345	6441.76467 2124.37341	F(1,18)=.443, p=.514, eta^2=.024
block 2	Shared control Human control	5282.1938 7439.6495	4072.19952 2603.86839	F(1,18)=1.992, p=.175, eta^2=.100
block 3	Shared control Human control	5026.2789 5487.1458	3407.24118 2505.34289	F(1,18)=.119, p=.734, eta^2=.007
block 4	Shared control Human control	4538.9603 3746.4376	3459.35288 1997.00525	F(1,18)=.394, p=.538, eta^2=.021
Wilks' Lambda=.496, F(4, 15)=3.81, p=025, eta^2=.504				

ANOVA Results in the last column are reported using the conventions in [40]: having probability (p) values much larger than 0.05 is a statistical indicator that shared and human control performances were not different in the blocks of day 1.

TABLE II
MEANS, STANDARD DEVIATIONS, AND POST HOC TEST USING THE BONFERRONI CORRECTION FOR COMPARISONS OF DAY 1 TO DAY 2, DAY 1 TO DAY 3, DAY 1 TO DAY 4, DAY 2 TO DAY 3, DAY 2 TO DAY 4 AND DAY 3 TO DAY 4 PERFORMANCES IN SHARED CONTROL CONDITION IS GIVEN

Pairs	Mean(mm)	Std. dev (mm)	sig (p value)
day1 **day2**	6138.8013 3450.5946	4003.30099 2028.87085	.125
day1 **day3**	6138.8013 2298.1561	4003.30099 1057.63405	**.029**
day1 **day4**	6138.8013 1733.2929	4003.30099 623.72900	**.028**
day2 **day3**	3450.5946 2298.1561	2028.87085 1057.63405	.110
day2 **day4**	3450.5946 1733.2929	2028.87085 623.72900	**.074**
day3 **day4**	2298.1561 1733.2929	1057.63405 623.72900	.690

Bold values in the sig column indicates that the subject performances on the corresponding day pairs are statistically different (marginally for the case of day 2–day 4).

tion of sphericity this correction was needed) for the correlation coefficients of the roll and pitch commands individually.

III. RESULTS

A. Group and Day-by-Day Performance

To answer the research question of whether there is any group mean difference in performance between shared control and human control conditions, we used the statistical package for the social sciences (SPSS) version 20, and we performed one-way MANOVA for four day's performances. The main objective in this analysis was to determine whether improvement in subject performances are altered by the experimental condition in which the subjects performed the task. The results of the analysis showed that for the first and second days, there was no significant difference between shared control and human control conditions in subjects' trajectory lengths. However, there were group mean differences for these two conditions in the subsequent days: The shared control condition group means of trajectory length were significantly lower than the ones in the human control condition for day three and four (see Fig. 4).

To find if the performance was the same in shared control and human control in the first day, we run one-way MANOVA over the first day experimental blocks. Results showed that although MANOVA was significant, follow-up ANOVAs for each block was not significant (see Table I). This means that there was no significant difference between shared control group mean and human control group mean in the performances measured by trajectory length for none of the four blocks in the first day.

Finally, to assess the progress over days for each condition, we ran a repeated measures ANOVA with a Greenhouse-Geisser correction (as our data violated the assumption of sphericity, this correction was applied) for shared control and human control conditions separately. Result showed that in the shared control condition trajectory length was significantly different among the days of experiment [$F(1.382, 12.442) = 11.658$, $p = .003$, $eta^2 = .564$].

As can be seen in Table II, Post hoc tests using the Bonferroni correction revealed that shared control condition trajectory lengths was significantly different for two comparisons of days and marginally significant for one comparison of days. That is, in shared control condition subjects showed significant progress with getting lower trajectory length day by day from day 1 → day 3 and day 1 → day 4 and day 2 → day 4 (marginally significant) (see Fig. 4 for the general trend).

Similarly, for also the human control condition, a repeated measures ANOVA with a Greenhouse-Geisser correction (again to compensate for the sphericity assumption violation) was performed. The results revealed that the trajectory length among the days of experiment was significantly different [$F(2.219, 19.968) = 11.959$, $p < .001$, $eta^2 = .571$]. As can be seen in Table III, Post hoc tests using the Bonferroni correction showed that human control condition trajectory lengths was significantly different for two comparisons of days. That is subjects in human control condition displayed significant progress with

TABLE III
MEANS, STANDARD DEVIATIONS, AND POST HOC TEST USING THE BONFERRONI CORRECTION FOR COMPARISONS OF DAY 1 TO DAY 2, DAY 1 TO DAY 3, DAY 1 TO DAY 4, DAY 2 TO DAY 3, DAY 2 TO DAY 4, AND DAY 3 TO DAY 4 PERFORMANCES IN HUMAN CONTROL CONDITION

Pairs	Mean(mm)	Std. dev (mm)	sig (p value)
day1	6238.4168	1711.29810	.304
day2	5005.7661	2650.08196	
day1	6238.4168	1711.29810	**.011**
day3	3908.4740	1741.27786	
day1	6238.4168	1711.29810	**.003**
day4	3894.1631	623.72900	
day2	5005.7661	2650.08196	.198
day3	3908.4740	1741.27786	
day2	5005.7661	2650.08196	.269
day4	3894.1631	1774.92222	
day3	3908.4740	1741.27786	1.00
day4	3894.1631	1774.92222	

Bold indicates statistical significance ($p \leq 0.05$).

getting lower trajectory length day by day from day 1 $\rightarrow$ day 3 and day 1$\rightarrow$ day 4 (see Fig. 4 for the general trend) paralleling shared control trend. However, in contrast to the shared control condition there was no marginally significant difference in performance measured by trajectory length between day 2 and day 4.

B. Learning Rate

The earlier analysis indicates that the learning progress between the shared control and human control are different. In this section, we try to quantify this by regression analysis by fitting regression models as a function of trial number for each subject. Three possible fit functions of linear, exponential, and power were considered. With each model, we regressed the performance data of each subject and noted the R^2 value (see Table V in appendix) to see which model was most suitable over the subject population. For most subjects, Power function seemed to represent best the learning curve for both human control and shared control subjects. Thus, we performed our population analysis of learning rate based on the power function. Typical fits for subject performances using power functions are given in Fig. 5.

The additive inverse of the *exponent* (i.e., *b)* in the power function ($y = ax^{-b}$) that was used to regresses the data (*x*: trial number; *y*: trajectory length) was taken as the "learning rate" for each subject. According to this definition, the subjects in the shared control condition had a higher learning rate (0.43 ± 017) than the subjects in human control condition (0.25 ± 0.15) on the average (Fig. 6).

To assess statistical significance, we performed *t*-test on the learning rates of shared control and human control subjects. The results confirmed that two groups are significantly different ($p < 0.022$); hence, shared control subjects learned faster than the human control subjects.

C. Compatibility of Human and Robot Commands in the Shared Control Condition

As the results reported above indicate that the performance of the human–robot system improves faster in the shared control

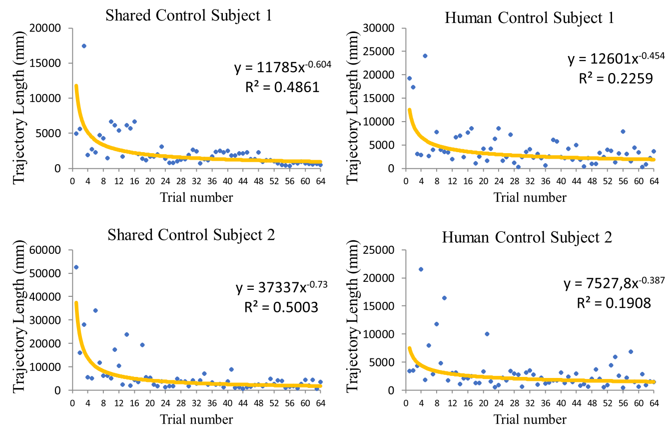

Fig. 5. Fitted power functions are shown for two subjects in shared control condition on the left and two subjects in human control condition on the right. Function parameters and R^2 values are also reported. The latter indicates the goodness of the fit (in regression analysis, R^2 is the proportion of the variance in the dependent variable that is predictable from the independent variable).

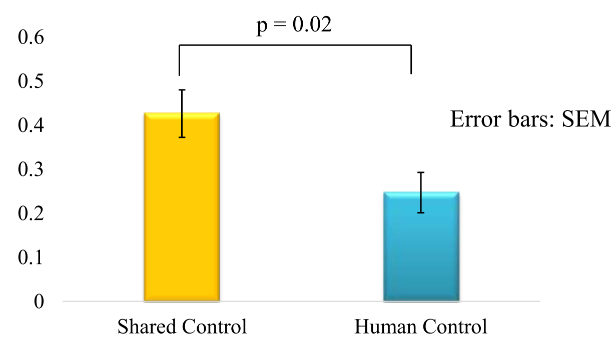

Fig. 6. Means and standard deviation of the mean for learning rate of human control and shared control condition conditions. A probability $p \leq 0.05$ indicates significant difference; i.e., we have strong statistical indication that learning rates of the subjects in the shared and human control conditions were different.

condition, the next question one might be interested in is, why this is so. Although there may be several human policies for improving the task execution performance, intuition says, at least subjects should learn not to conflict with the robot. To check this hypothesis, we investigated the change of linear correlation between human and robot actions over days in the shared control condition for *roll* and *pitch* commands. The results show that in general, the correlation between the human and robot commands increased via learning. The details of the analysis are as follows:

Roll command *correlation*: Statistical (repeated measures ANOVA) analysis revealed that the correlation coefficient of *roll* between the days was significantly different [F (2.011, 18.098) $= 7.501$, $p = .004$, eta2 $= .455$]. Moreover, post hoc tests using the Bonferroni correction showed that for *roll*, correlation coefficient between the human and robot commands was significantly different for two comparisons of the days in the shared control condition (see Table IV). To be concrete, the correlation coefficient of *roll* had a significant increase from day1 to day 4 and day 2 to day 4 with an overall significant linear trend over days [$F(1, 9) = 28.699$, $p = .000$, eta2 $= .761$].

TABLE IV
MEANS, STANDARD DEVIATIONS, AND POST HOC TEST USING THE BONFERRONI CORRECTION FOR COMPARISONS OF DAY 1 TO DAY 2, DAY 1 TO DAY 3, DAY 1 TO DAY 4, DAY 2 TO DAY 3, DAY 2 TO DAY 4, AND DAY 3 TO DAY 4 ARE GIVEN FOR THE CORRELATION COEFFICIENTS BETWEEN THE HUMAN AND ROBOT *ROLL* AND *PITCH* MOTOR COMMANDS IN THE SHARED CONTROL CONDITION

	Correlation coefficient: ***roll***			Correlation coefficient: ***pitch***		
Pairs	Mean	Std.dev	sig	Mean	Std.dev	sig
day1	.0762	.0556	1.00	.0624	.0469	1.00
day2	.0748	.0567		.0654	.0391	
day1	.0762	.0556	1.00	.0624	.0469	1.00
day3	.0818	.0635		.0727	.0600	
day1	.0762	.0556	**.001**	.0624	.0469	**.061**
day4	.1164	.0523		.0900	.0498	
day2	.0748	.0567	1.00	.0654	.0391	1.00
day3	.0818	.0635		.0727	.0600	
day2	.0748	.0567	**.040**	.0654	.0391	.325
day4	.1164	.0523		.0900	.0498	
day3	.0818	.0635	.169	.0727	.0600	.261
day4	.1164	.0523		.0900	.0498	

Bold probability values under sig columns indicate statistical significance (marginal significance for the pitch case).

Pitch command *correlation:* Statistical analysis showed that the correlations coefficient of *pitch* between days was significantly different [F (3, 27) = 3.545, p = .028, eta2 = .283]. However, as seen in Table IV, Post hoc tests using the Bonferroni correction showed that correlation coefficient of *pitch* between human and robot commands was not significantly different for any comparisons of the days in the shared condition, although there was a marginally significant increase from day 1 to day 4. That is, although the correlation coefficient of *pitch* has an increasing linear trend [F (1, 9) = 6.886, p = .028, eta2 = .433], unlike the *roll*, no significant day to day improvement was observed in the pitch motor command.

IV. CONCLUSION

In this paper, we considered a synergistic human–robot collaboration system with a simple human intention inference mechanism. Then, we investigated the effect of this system on task execution performance and human sensorimotor learning by realizing it for "ball balancing task" where a ball had to be balanced on a tray held by an anthropomorphic robot arm. To assess the efficacy of our collaborative setup, two control scenarios were considered. In the first one, a human was in the control loop generating teleoperative control commands, where the robot passively followed the commands (human control condition). In the second control scenario, a human–robot shared control system was created where the robot system tried to predict the human intention, and based on that, generate motor commands that are combined with the human generated commands in real-time to drive the robot. From a sensorimotor adaptation point of view, the former system is much easier for humans to master as the system (i.e., robot) controlled is stationary and has a well-defined response. However, in the latter scenario, humans need to interact with a partner whose behavior is not clear to them at the beginning, and mastery can be achieved when the behavior of the robot is learned by the human. Therefore, from the beginning, it is not clear which scenario will lead to a better performance, and what will be the course of human sensorimotor learning in these two conditions. Thus, to assess the effect of the implemented shared control system on collaborative task performance and human adaptation, we conducted experiments for each of the scenarios (10 subjects for each condition) and observed the performances of the subjects over four days. The results showed that at the onset, the usual robot teleoperation and the condition where the robot shared control by estimating the human intention, the task performance was comparable; i.e., in the first day human control and shared control condition group performances were not statistically different. However, after four days of task execution, the performance of the human–robot shared control system was clearly much higher than the human-only control condition. There was a different day by day learning trend between shared control and human control conditions. Literally, there was no improvement at all from day-three to day-four in the human control condition whereas there was a visible improvement in the shared control condition, which is supported by the fact that the improvement from day-two to day-four in the shared control condition is marginally significant (p = 0.074) whereas in the human control condition it is not significant (p = 0.27).

It is intriguing to know what kind of human policy made the shared control performance better. A good policy should not conflict with the robot commands. Therefore, as learning progresses the compatibility between the robot and the human motor commands should increase. The analyses conducted to verify this logic indicated that indeed the correlation between the human and robot commands increased. To be specific, for the *roll* component of the motor command significant increase across days could be detected, whereas for the *pitch* component, although a linear increase trend can be observed, no statistical significance could be found across days (only a marginal significance of p = 0.061 from day-one to day-four was found). Although, the current analysis does not allow us to pinpoint the form of the policies acquired by the subjects, we can say that the learning resulted in reduced conflict with robot commands.

Overall, the results suggest that humans, along with learning task execution, can learn the behavior of the robot so as to exploit it as an assistive partner. Consequently, this results in faster learning and higher task performance given the same amount of learning. This is especially interesting considering that the initial difficulty in dealing with the complex behavior of the robot due to the goal estimation mechanism is offset by the human sensorimotor learning. Therefore, the adoption of such synergistic human–robot shared control systems may be the key for their wide deployment in applications where expert human operation of a machine is required. Simply put, this framework will not only reduce the training cost of a beginner operator to make him/her an expert, but also increase the performance of the human–machine system beyond that can be achieved by the human operator alone.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

V. Discussion

In a shared control system, the decision mechanism of who should be in control, when and how much, is one of the major factors that determines the usability and efficiency of the system. The decision can be based on a range of factors or parameters, such as completion of predetermined task specific check points, overall task performance, or deliberate human involvement. In scenarios, where a clear distinction exists as to where (in state space) human and the robot has expertise, a continuous weight sharing over the control signals may not be suitable; instead, an automatic switching control can be used to switch the control between the human and the robot. In other cases, human may tune the weight sharing parameter manually, say to get more assistance from the robot when desired or to be fully in charge. A common simple shared control system mechanism is cruise control, where the human has the say on when to get help for speed regulation. In this case, the automobile's behavior is extremely simple. In general, when two agents should coordinate to generate a high performing team, an adaptation mechanism to learn the partner's behavior is needed. In the human case, this mechanism is readily implemented by the central nervous system. This is true even for human–human collaborative systems; in fact, prediction and modeling others' behavior is at the center of human intelligence and dexterity. Therefore, the main goal of shared control systems must be not only to enhance the capacity and skill of the collaborating machine or robot, but also to make it easy for humans to model and thus exploit the behavior of the collaborating agent.

When subjects' trajectories from our experiments are inspected, it appears that shared control subjects showed a sharp performance improvement after an initial exploration phase. We attribute this to the possibility that they could model and adapt to the behavior of the robot and exploit it in the subsequent trials for improved performance. After the last day of the experiments, we also had subjects fill a questionnaire. One of the questions there asked whether subjects became aware of the behavior of the robot. The verbal answers to this question were classified as negative (blocking), neutral (no help), and positive (helping). As a result, 9 out of 10 subjects in the human control condition, reported neutral as expected. In the shared control condition, 9 out of 10 subjects reported that robot was involved in control. However, one of the 9 subjects indicated that the robot was a hindrance when he tried to move fast. Overall, the reports from the shared control subjects indicate that subjects "understood" the robot behavior; and one of the subjects explicitly indicated that the robot was helpful when he was moving slow. This observation is interesting; because it reflects a fact that we did not expect the subjects would realize: the robot controller balances the ball by using a policy (taught by a human demonstrator) that slowly brings the ball to the target location; hence, its control output would conflict with a human operator that wishes to make fast movements. Finally, it is worth noting that human realization and exploitation of the robot behavior happened rapidly, i.e., in the first day.

After understanding that the robot *can* help, a simple strategy in the current task could be to "hint" the robot the correct location in the initial part of the trajectory and thereafter have the robot complete the task almost alone by applying slight corrections only when needed. Another alternative would be to make a fair share with the robot and always try to be in-synch with the robot. Our results suggest that the latter strategy is partially adopted by the shared control subjects: for the *roll* command, we see a significant increase in the correlation between the human and motor control outputs when comparing day 1 and 2 to day 4; however, we do not see such a significant increase in the *pitch* command. Although a larger population may lead to a significant change in the *pitch* command, we believe that there will be individual differences on how exactly the subjects utilize the robot for the benefit of task performance.

Therefore, it seems worthwhile to design experiments specifically to uncover the range of human mechanisms of exploiting a given partner robot. In those studies, metrics other than linear correlation should be sought to assess potentially more complex interaction patterns between the subjects and the robot.

In the current study, although the robot had a nontrivial behavior, it did not try to predict or copy human actions for better performance. Making the robot adapt to, or learn from its human partner, while the human is also learning the task and robot behavior, is one of the most interesting research topics that needs to be addressed (see [5] and citation therein for the recent developments in this front). The interaction in this case would be much richer; but the challenge then would be to guarantee convergent behavior of the human–robot system, while ensuring significant improvement in task performance with reduced human effort.

As a final note, studying and exploiting the multimodal nature of shared control seems to be a fruitful research area, in particular due to the fact that mixing of modalities is possible. For example, one can feedback position information as a haptic or an auditory sensation to the human operator. Likewise, the output of a positional interface, such as a regular joystick may be mapped to force references on the robot. In general, haptic control systems are intrinsically well-suited for force control tasks (e.g., [41]–[43]). In addition, multimodal full body feedback interfaces [15], [44] are natural choices when full-body tasks are targeted. Going back to our ball balancing task, we can expect a haptic control joystick to be ideal for controlling and sensing the tilt of the tray that would probably allow faster learning in the human control condition. However, it is still an open question how the shared control adaptation will ensue and should be explored in future studies.

Other control interface alternatives do exist. For example, in one extreme, one can envision that the position of the ball can be feedback to the robot via localized audio or vibro-tactile sensors (e.g., [45], [46]). On the other hand, the tray can be controlled through direct movement of some body part by the help of a motion capture system; e.g., waist (as in [15]), wrist, arm, or finger movements can be used. Depending on the body part, information bandwidth differs [47]; but alone this is not sufficient to assess suitability as the anthropomorphic compatibility of the robot with the limb is likely to affect cognitive and motor load, which should be investigated from both behavioral and neuroscientific viewpoints (see [48] for an initial attempt). We predict that with wide adoption of human-in-the-loop shared control systems, neuroscience of shared-control will be a mainstream multidisciplinary research track in the near future.

APPENDIX

TABLE V
"R^2" VALUE FOR THREE DIFFERENT REGRESSION MODELS FOR EACH SUBJECT. BEST FIT COLUMN INDICATES THE BEST MODEL FOR EACH SUBJECT. OVERALL, POWER FUNCTION FIT WAS FOUND TO BE THE BEST MODEL FOR BOTH SHARED CONTROL AND HUMAN CONTROL GROUPS

Condition	Subject	R^2 for the fitted regression function			Best Fit
		Linear(l) $y = ax + b$	Exponential(e) $y = ae^{bx}$	Power(p) $y = ax^b$	
Shared Control	Subject 1	0.33	0.5478	0.4861	e
	Subject 2	0.2762	0.3833	0.5003	p
	Subject 3	0.2104	0.1981	0.2547	p
	Subject 4	0.1393	0.1116	0.1761	p
	Subject 5	0.388	0.407	0.3014	e
	Subject 6	0.2588	0.2777	0.2778	p
	Subject 7	0.1623	0.0767	0.0732	e
	Subject 8	0.1498	0.0794	0.1492	l
	Subject 9	0.2153	0.2333	0.3057	p
	Subject10	0.2196	0.2254	0.2723	p
Human Control	Subject 1	0.016	0.0069	0.0527	p
	Subject 2	0.1343	0.1593	0.1908	p
	Subject 3	0.0939	0.0391	0.1424	p
	Subject 4	0.2052	0.1065	0.1101	l
	Subject 5	0.1267	0.0905	0.0946	l
	Subject 6	0.002	0.00008	0.006	p
	Subject 7	0.133	0.1747	0.1606	e
	Subject 8	0.0048	0.0017	0.0005	l
	Subject 9	0.1885	0.1656	0.2259	p
	Subject10	0.0495	0.0172	0.0238	l
Average		**0.16518**	**0.165094**	**0.19021**	**p**

REFERENCES

[1] L. Peternel, T. Petric, E. Oztop, and J. Babic, "Teaching robots to cooperate with humans in dynamic manipulation tasks based on multi-modal human-in the-loop approach," *Auton. Robots*, vol. 36, no. 1–2, pp. 123–136, 2014.

[2] A. D. Dragan and S. S. Srinivasa, *Formalizing Assistive Teleoperation*. Cambridge, MA, USA: MIT Press, Jul. 2012.

[3] A. D. Dragan and S. S. Srinivasa, "A policy-blending formalism for shared control," *Int. J. Robot. Res.*, vol. 32, no. 7, pp. 790–805, 2013.

[4] N. Amirshirzad, O. Kaya, and E. Oztop, "Synergistic human-robot shared control via human goal estimation," in *Proc. IEEE 55th Annu. Conf. Soc. Instrum. Control Eng. Jpn.*, 2016, pp. 691–695.

[5] S. Nikolaidis, D. Hsu, and S. Srinivasa, "Human-robot mutual adaptation in collaborative tasks: Models and experiments," *Int. J. Robot. Res.*, vol. 36, no. 5–7, pp. 618–634, 2017.

[6] V. A. Shia *et al.*, "Semiautonomous vehicular control using driver modeling," *TITS*, vol. 15, no. 6, pp. 2696–2709, Dec. 2014.

[7] M. Kuderer, S. Gulati, and W. Burgard, "Learning driving styles for autonomous vehicles from demonstration," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2015, pp. 2641–2646.

[8] L. Peternel, T. Noda, T. Petrič, A. Ude, J. Morimoto, and J. Babič, "Adaptive control of exoskeleton robots for periodic assistive behaviours based on EMG feedback minimisation," *PLoS One*, vol. 11, no. 2, Feb. 2016, Art. no. e0148942.

[9] Z. Wang *et al.*, "Probabilistic movement modeling for intention inference in human-robot interaction," *Int. J. Robot. Res.*, vol. 32, no. 7, pp. 841–858, 2013.

[10] D. Kushida, M. Nakamura, S. Goto, and N. Kyura, "Human direct teaching of industrial articulated robot arms based on force-free control," *Artif. Life Robot.*, vol. 5, no. 1, pp. 26–32, 2001.

[11] J. Saunders, C. L. Nehaniv, K. Dautenhahn, and A. Alissandrakis, "Self imitation and environmental scaffolding for robot teaching," *Int. J. Adv. Robot. Syst.*, vol. 4, no. 1, 2007, Art. no. 14.

[12] J. Saunders, C. L. Nehaniv, and K. Dautenhahn, "Teaching robots by moulding behavior and scaffolding the environment," in *Proc. 1st ACM SIGCHI/SIGART Conf. Human–Robot Interact.*, 2006, pp. 118–125.

[13] B. Moore and E. Oztop, "Robotic grasping and manipulation through human visuomotor learning," *Robot. Auton. Syst.*, vol. 60, no. 3, pp. 441–451, 2012.

[14] E. Ugur, Y. Nagai, E. Sahin, and E. Oztop, "Staged development of robot skills: Behavior formation, affordance learning and imitation with motionese," *IEEE Trans. Auton. Mental Develop.*, vol. 7, no. 2, pp. 119–139, 2015.

[15] J. Babic, J. G. Hale, and E. Oztop, "Human sensorimotor learning for humanoid robot skill synthesis," *Adaptive Behav.*, vol. 19, no. 4, pp. 250–263, 2011.

[16] E. Oztop, L.-H. Lin, M. Kawato, and G. Cheng, "Extensive human training for robot skill synthesis: Validation on a robotic hand," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2007, pp. 1788–1793.

[17] Y. Inagaki, H. Sugie, H. Aisu, S. Ono, and T. Unemi, "Behavior-based intention inference for intelligent robots cooperating with human," in *Proc. IEEE Int. Conf. Fuzzy Syst.*, 1995, vol. 3, pp. 1695–1700.

[18] M. Tomasello, M. Carpenter, J. Call, T. Behne, and H. Moll, "Understanding and sharing intentions: The origins of cultural cognition," *Behav. Brain Sci.*, vol. 28, no. 05, pp. 675–691, 2005.

[19] C. Vesper, S. Butter_ll, G. Knoblich, and N. Sebanz, "A minimal architecture for joint action," *Neural Netw.*, vol. 23, no. 8, pp. 998–1003, 2010.

[20] D. T. McRuer, "Pilot-induced oscillations and human dynamic behavior," Systems Technology, Inc., Hawthorne, CA, USA, Tech Rep. TR-2494-1, 1995, vol. 4683.

[21] M. Saffarian, J. C. de Winter, and R. Happee, "Automated driving: Human-factors issues and design solutions," in *Proc. Human Factors Ergonom. Soc. Annu. Meet.*, vol. 56, Los Angeles, CA, 2012, pp. 2296–2300.

[22] N. B. Sarter and D. D. Woods, "Team play with a powerful and independent agent: Operational experiences and automation surprises on the airbus a-320," *Human Factors: J. Human Factors Ergonom. Soc.*, vol. 39, no. 4, pp. 553–569, 1997.

[23] J. Yen, X. Fan, S. Sun, T. Hanratty, and J. Dumer, "Agents with shared mental models for enhancing team decision makings," *Decis. Support Syst.*, vol. 41, no. 3, pp. 634–653, 2006.

[24] L. B. Rosenberg, "Virtual fixtures: Perceptual tools for telerobotic manipulation," in *Proc. IEEE Virtual Reality Annu. Int. Symp.*, 1993, pp. 76–82.

[25] P. Aigner and B. McCarragher, "Human integration into robot control utilising potential fields," in *Proc. IEEE Int. Conf. 1997 Robot. Autom.*, vol. 1, 1997, pp. 291–296.

[26] T. Debus, J. Stoll, R. Howe, and P. Dupont, "Cooperative human and machine perception in teleoperated assembly," in *Proc. 5th Int. Symp.*, Honolulu, HI, 2000, pp. 51–60.

[27] J. W. Crandall and M. A. Goodrich, "Characterizing efficiency of human robot interaction: A case study of shared-control teleoperation," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, vol. 2, 2002, pp. 1290–1295.

[28] P. Marayong, A. Bettini, and A. Okamura, "Effect of virtual fixture compliance on human-machine cooperative manipulation," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, vol. 2, 2002, pp. 1089–1095.

[29] P. Marayong, M. Li, A. M. Okamura, and G. D. Hager, "Spatial motion constraints: Theory and demonstrations for robot guidance using virtual fixtures," in *Proc. IEEE Int. Conf. Robot. Autom.*, vol. 2, 2003, pp. 1954–1959.

[30] J. Kofman, X. Wu, T. J. Luu, and S. Verma,"Teleoperation of a robot manipulator using a vision-based human-robot interface," *IEEE Trans. Ind. Electr.*, vol. 52, no. 5, pp. 1206–1219, Oct. 2005.

[31] E. You and K. Hauser, "Assisted teleoperation strategies for aggressively controlling a robot arm with 2d input," *Robot.: Sci. Syst.*, vol. 7, 2012, Art. no. 354.

[32] D. J. Kim *et al.*, "How autonomy impacts performance and satisfaction: Results from a study with spinal cord injured subjects using an assistive robot," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 42, no. 1, pp. 2–14, Jan. 2012.

[33] J. Demiris and G. Hayes, "Imitation as a dual-route process featuring predictive and learning components; 4 biologically plausible computational model," in *Imitation in Animals and Artifacts*. Cambridge, MA, USA: MIT Press, 2002, pp. 327–361.

[34] M. Li and A. M. Okamura, "Recognition of operator motions for real-time assistance using virtual fixtures," in *Proc. IEEE 11th Symp. Haptic Interfaces Virtual Environ. Teleoperator Syst*, 2003, pp. 125–131.

[35] A. Fagg, M. Rosenstein, R. Platt, and R. Grupen, "Extracting user intent in mixed initiative teleoperator control," in *Proc. AIAA 1st Intell. Syst. Tech. Conf.*, 2004, Electronically published.

[36] W. Yu, R. Alqasemi, R. Dubey, and N. Pernalete, "Telemanipulation assistance based on motion intention recognition," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2005, pp. 1121–1126.

[37] D. Aarno, S. Ekvall, and D. Kragic, "Adaptive virtual fixtures for machine assisted teleoperation tasks," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2005, pp. 1139–1144.

[38] T. Taha, J. V. Miro, and G. Dissanayake, "Pomdp-based long-term user intention prediction for wheelchair navigation," in *Proc. IEEE Int. Conf. Robot. Automat.*, 2008, pp. 3920–3925.

[39] A.-B. Karami and A.-I. Mouaddib, "A decision model of adaptive interaction selection for a robot companion.," in *Proc. 5th Eur. Conf. Mobile Robots*, 2011, pp. 83–88.

[40] B. G. Tabachnick and L. S. Fidell, *Using Multivariate Statistics*, 6th ed. Boston, MA, USA: Pearson Education, 2013.

[41] P. Evrard, E. Gribovskaya, S. Calinon, A. Billard, and A. Kheddar, "Teaching physical collaborative tasks: Object-lifting case study with a humanoid" in *Proc. IEEE-RAS Int. Conf. Humanoid Robots*, 2009, pp. 399–404.

[42] A. Ajoudani, N. Tsagarakis, and A. Bicchi, "Tele-impedance: Teleoperation with impedance regulation using a body–machine interface," *Int. J. Robot. Res.*, vol. 31, no. 13, pp. 1642–1656, 2012.

[43] L. Peternel, E. Oztop, and J. Babic, "A shared control method for online human-in-the-loop robot learning based on locally weighted regression," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2016, pp. 3900–3906.

[44] L. Peternel and J. Babic, "Learning of compliant human-robot interaction using full-body haptic interface," *Adv. Robot.*, vol. 27, no. 13, pp. 1003–1012, 2013.

[45] A. Wachaja, P. Agarwal, M. Zink, MR. Adame, K. Möller, W. Burgard, "Navigating blind people with a smart walker," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2015, pp. 6014–6019.

[46] A. Cosgun, E. A. Sisbot, and H. I. Christensen, "Guidance for human navigation using a vibro-tactile belt interface and robot-like motion planning," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2014, pp. 6350–6355.

[47] R. Balakrishnan and I. Scott MacKenzie, "Performance differences in the fingers, wrist, and forearmin computer input control," in *Proc. ACM SIGCHI Conf. Human Factors Incomput. Syst.*, 1997, pp. 303–310.

[48] E. Oztop, E. Ugur, Y. Shimizu, and H. Imamizu, "Humanoid robotics and neuroscience: Science, engineering and society," in *Humanoid Brain Science*, G. Cheng, Ed. Boca Raton, FL, USA: CRC Press, 2015, pp. 29–48.

Negin Amirshirzad received the bachelor's degree in computer engineering from Shahid Beheshti University, Tehran, Iran, in 2014, and the M.Sc. degree in computer science from Ozyegin University, Istanbul, Turkey, in 2017. She is currently working toward the Ph.D. degree in computer science at Ozyegin University.

Asiye Kumru received the M.A. and Ph.D. degrees in developmental psychology from the University of Nebraska-Lincoln, Lincoln, Nebraska, in 1998 and 2002, respectively.

She is currently a Professor in developmental psychology with Ozyegin University, Istanbul, Turkey. Her research interests include prosocial and moral development, socioemotional development, attachment, gender socialization, and identity development.

Erhan Oztop received the Ph.D. degree from the University of Southern California, Los Angeles, CA, USA, in 2002. He researched and led several research groups at Advanced Telecommunications Research Institute International, Kyoto, Japan during 2002–2011. Then, he joined Ozyegin University in Istanbul, Turkey as a faculty member, where he is currently serving as the Chair of the Computer Science Department.