# HUMAN-ROBOT COLLABORATION FOR SYNERGISTIC TASK EXECUTION

A Thesis

by

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Submitted to the
Graduate School of Sciences and Engineering
In Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in the
Department of Computer Science

Özyeğin University
May 2017

# HUMAN-ROBOT COLLABORATION FOR SYNERGISTIC TASK EXECUTION

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# ABSTRACT

There is great potential for human and robot to work together as a team, since this collaboration can take advantage of both human and robot capabilities, cover their weakness and yield a higher performance. We propose and implement a human-robot collaboration framework where, while the human tries to perform a task, the robot infers the human intention and assists the human in achieving the inferred goal. We explore how the human is influenced when (s)he interact with machine autonomy, and whether there is any advantage in task performance when human shares control with an autonomous agent. In particular, we investigate whether interacting with autonomy can aid humans to improve their performance in shorter time. We realized this collaboration system by designing a ball balancing task in which the goal is to move and balance the ball on a target position on a tray held by a robotic arm. The human performs the task by controlling the robotic arm with an interface which tilts the tray and moves the ball while the robot infers the target ball position by observing the trajectory of the ball, and augments the human control commands for assisting in task execution. The length of ball movement trajectory, completion time and positional error were chosen as the measures to evaluate the task performance. To assess the impact of our system on human learning and task execution a set of experiments were conducted under two conditions, human control condition where human performs the task alone and share control condition where both human and robot are involved in performing the task. 20 naive subjects were volunteered to perform the experiment in four continuous days. The result of these experiments suggests that not only the task execution can be improved in collaboration with robot compare to when the humans perform the task alone but also this collaboration system can make the human learning to progress faster.

# ÖZETÇE

İnsan ve robotun takım olarak çalışması ve etkileşimde bulunması büyük bir potansiyeldir, çünkü bu işbirliği hem insan hem de robot yeteneklerinden yararlanabilir, iki tarafın zayıf noktalarını giderir ve daha yüksek bir performans verir. Bu tezde insanın görevi yerine getirmeye çalışırken, robotun onun niyetini bularak hedefe ulaşmasına yardımcı olan, bir insan-robot işbirliği çerçevesi önerilmiş ve uygulamısı gösterilmiştir. İnsanın, makine özerkliği ile etkileşime girmesi durumunda nasıl etkilendiği ve insanın özerk bir ajanla olan paylaşımlı kontrolünün performansa herhangi bir avantaj sağlayıp sağlamadığı konuları çalışılmıştır. Özellikle, özerklik ile etkileşimin insanlara daha kısa sürede performanslarını artırmalarına yardımcı olup olamayacağı araştırılmıştır. Bu işbirliği sistemini, robot kolunun tuttuğu bir tepsi üzerinde topu hareket ettirerek istenilen konumda dengelemeye çalışan top dengeleme görevi tasarlayarak gerçekleştirdik. İnsan robot kolunu, tepsiyi eğen ve topu hareket ettiren bir arayüzle kontrol ederek görevi yerine getirirken, robot topun yörüngesini izleyerek insanın niyet ettiği top pozisyonunu öngörür ve görev icrasında yardımcı olmak için insan kontrol çıktısına ekleme yapar. Bu çalışmada görev performansını değerlendirmek için topun hareket yörüngesi uzunluğu, görevin tamamlanma süresi ve topun konumsal hatası seçildi. Sistemimizin insan öğrenimi ve görev icrası üzerindeki etkisini değerlendirmek için, insanların görevleri tek başına yerine getirdiği ve paylaşımlı kontrol koşullarıyla hem insan hem de robotun görevi yerine getirdiği iki koşul altında bir dizi deney gerçekleştirildi. Dört devamlı gün içinde deneyi gerçekleştirmek için 20 kişi gönüllü oldu. Bu deneylerin sonucu, yalnızca insanların, görevi tek başına gerçekleştirdiği zamana kıyasla, robot işbirliği içinde daha iyi yürütülebileceğini ve aynı zamanda bu işbirliği sisteminin insan görev öğrenimini hızlandırdığını göstermiştir.

# ACKNOWLEDGEMENTS

First and foremost I would like to thank my advisor, Dr.Erhan Öztop, head of Computer Science department at Özyeğin University. It has been a great honor to be your M.Sc. student. You supported me greatly and taught me both consciously and unconsciously. I want to thank you for the excellent guidance, care, patience, and the opportunity I was given to conduct my research. My research experience under your supervision was very exciting and fun, and has motivated me to be a passionate professor and researcher as you are. I sincerely hope that I continue to have opportunities to interact with you for the rest of my research career.

Besides my advisor, I should express my deepest gratitude to my thesis committee members: Dr.Emre Uğur and Dr.Asiye Kumru. Thank you for your intellectual contribution and devoting your time to me. I am also very appreciative of Dr.Asiye Kumru for her kind help in statistical analysis of this work. I should sincerely thank Dr.Özkan Bebek for his help in the experimental setup.

The members of the OZU Robotics Lab have contributed immensely to my personal and professional time at Özyeğin. I should thank Awais Ahmad and Osman Kaya for being such good colleagues and friends. You were always supportive and willing to help, it would have been a lonely lab without you guys.

I gratefully acknowledge the funding sources that made my M.Sc. work possible. I was funded by Özyeğin University and European Community's Seventh Framework Programme FP7/2007-2013 under the grant agreement no. 321700, Converge.

Lastly, I would like to thank my family and dear friends for all their love, support and encouragement.

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# Chapter I

# INTRODUCTION

## 1.1 Motivation

Some tasks might be out of human physical capabilities due to environmental risks and constraints or extreme accuracy requirements, and even though robots are expected to used in our daily life substantially in the coming decades, it is still hard or sometimes impossible to make some tasks completely and perfectly automated. Hence, there is a great potential for humans and robots to work together in a team as partners to contribute to given task objective based on their own individual capabilities rather than humans treating robots only as tools.

A robot used to be viewed as a device which performs physical tasks on command with human supervision, however, now we envision robots that can cooperate with humans as capable partners. Examples of such tasks include fly-by-wire aircraft control systems [1], automobiles with driver assistance systems [2] and medical devices [3]. Such interactive control systems can be referred as the human-in-the-loop control systems. While completion of such tasks in a totally autonomous fashion is desirable, it is not yet due to the dynamic operating situations and conditions, where it requires human administration or supervision. For example a robot is able to work autonomously under normal situations, however in unexpected or abnormal situations the robot may fail to operate and the human may need to interfere to make decisions on behalf of the robot, which can provide the system with the ability to deal with unexpected events. Even though self-driving vehicles are becoming a reality there are problems when unexpected things- the near misses, the bad weather, the fog, the rain, the snow, the dirty windshields, all of these things, may happen. For example consider the situation in which a mobile robot is driving outside, when it detects tall grass as a new surface to drive on, the robot itself may be unable to proceed and decide. However, if the robot is able to discuss the situation with a human and get a prompt response, a better solution can be found. Therefor a realistic solution involves a semi-autonomous control that works with the assistance of one or more human operators [4]. For example in [5] a system is developed that enables a team of robots to autonomously perform assembly manufacturing tasks, asking a human worker for help only when needed. This system enables robots to make requests intelligently and in a way that allows a human to easily comply with these requests. This uses concept of human-in-the-loop control to achieve greater robot capabilities than would be possible with a pure autonomous system. By adapting autonomy and human-robot interaction to the situation and the user, we can create systems which are easier to use and better performing. There are certain features in which humans are better and probably always will be superior to robots, such as flexibility, dexterity, perception, intuitive control, and high-level decision making, on the other hand, robots are resistant to hazards, robust to fatigue and good at precise low-level motion planning and repetitive tasks. Therefor interaction and combining human and robot skills seems very appealing, and the investigation of new shared control methods that can effectively blend the control between the human and the robot will make it possible to take advantage of these features and enables human-robot systems to surpass both robot and human performance.

## 1.2 Previous Works

A simple way to interact with robot is so called direct control [6–8], where the human controls the robot by physically holding and moving it through desired postures. Direct control is limited and not suitable for dynamic control tasks [9], and thus might be difficult to be widely adopted for shared control applications. In human-in-the-loop control [10–12], the human takes share in real-time control of the robot in order to make the robot perform a given task. However, no physical contact with the robot is needed. This paradigm has been successfully used to obtain robot skills such as ball manipulation [9] with a five fingered robotic hand, balanced inverse kinematics on a humanoid robot [11], and tasks involving force based policies [11,12]. In these studies human-in-the-loop control framework was used to obtain an autonomous controller for the robot and eventually remove the human from the control loop. However, in assistive 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 [13, 14], whereas in the latter a synergistic coupled system is formed by the human and the robot to perform the desired task [15]. Humans and robots can have a common goal and work cooperatively through perception, recognition and intention inference [16]. Collaboration hinges on coordination and the ability of partners to infer each other's intentions and also adapt [17, 18]. Coordination error and miscommunication between the human and autonomous agent will result in system failure [19–21]. Hence, ensuring that they have the ability to properly anticipate the needs and goals of each other from behavior during collaborative work is critical to achieving good team performance [22]. In prior work in human robot interaction and assistive teleoperation, it is usually assumed that the robot knows the human intention [23–31]. In some other works it is assumed that the human is following one of a set of predefined goals or paths, and then it trains a classifier for prediction [32–38]. Some frameworks assume certain behavior patterns of the human, a formalism for the robot assistance as an arbitration of two policies, namely, the user input and the robot prediction of the user intent, known as policy blending; has been shown to be effective [13, 14], this policy blending with accurate prediction has a strong corrective effect on the user input, the robot observes the human actions and finds the targeted goal among a set of potential ones from the human movement directions as both human and robot move towards their respective goals.

Our approach differs from these works in a way that it incorporates intention inference capability for the robot without the existence of any pre-defined goal or path to the goal. In addition to that we are also exploring how the human is influenced when interacts with machine autonomy. We explore if there is any advantage in task performance when human shares control with machine and how they progress and adapt to the system. We are also questioning if autonomy can aid humans to improve their performance higher and faster.

## *1.3 Thesis Outline*

**Chapter II** defines our general framework and methodology. First we propose a shared control framework. Then we design a task to implement and examine our proposed framework on. Then we explain the methods and robotic setup in detail, and finally we show how we implemented the proposed shared control framework on the physical designed task.

**Chapter III** presents our experiments and the results, and includes statistical analysis on the collected data to verify the efficiency of our proposed shared control framework.

**Chapter IV** concludes this thesis and discusses the possible directions for future work.

# Chapter II

# METHODOLOGY

## 2.1 Shared Control Framework

In our proposed framework the robot assists the human to accomplish a given task by inferring the human intention. The human starts performing the task, and simultaneously the robot starts estimating the human goal, taking share in control generating control commands and augmenting the human control commands based on its estimated goal. The control command that drives the robot is a combination of the robot and human command. In this work, we adopted the convex combination of the human and the robot generated commands to obtain the net motor command sent to the robot. To be concrete, the net command is given by $C_{net} = \omega C_H + (1 - \omega) C_R$) where $\omega$ is a parameter for sharing the control command weights, $C_H$ is the human command, $C_R$ is the robot command. Other control sharing schemes are clearly possible, including for example adaptive control sharing [39]. Our proposed framework is illustrated in Figure 1 where the plus sign in the control blending is used figuratively.

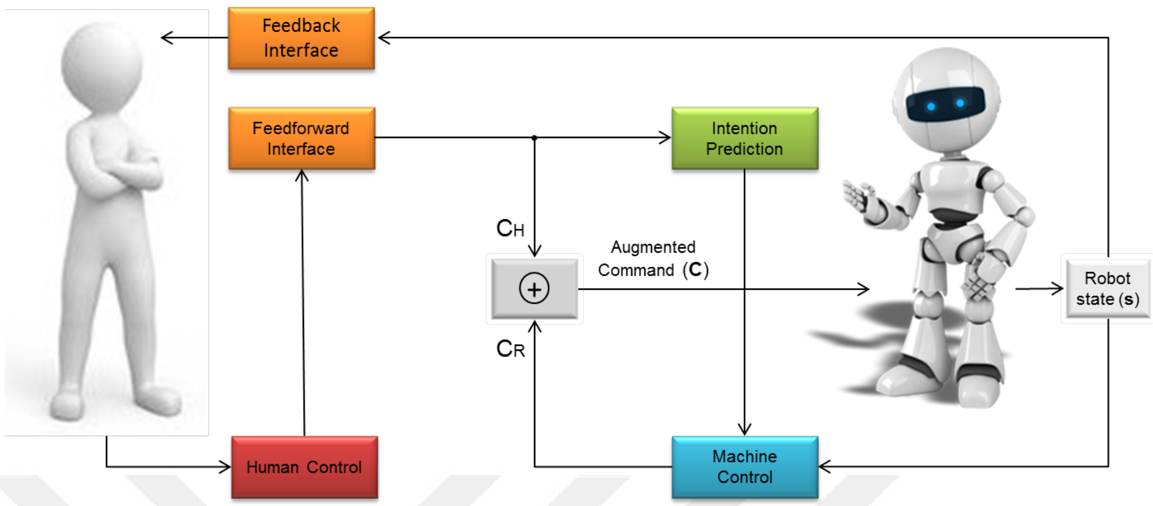


**Figure 1:** In this framework human operator controls the robot in real-time to achieve the desired goal. Simultaneously, the robot infers the human intention and generates commands based on its predicted goal to assist the human in achieving the task.

## 2.2 Designed Task

We realized the proposed framework by using a ball balancing task. In this designed task a tray is held by a robotic arm and a ball will be placed in the center of the tray in the beginning of the task. A desired target position is marked on the tray and the goal is to move and balance the ball on the desired target position by tilting the tray and teleoperating the robotic arm by using a computer mouse. This teleoperation is explained more in section 2.3.1. For combining the human and motor command, the convex combination is used with equal human and robot share (i.e. $\omega$ is chosen as 0.5 in $C_{net} = \omega C_H + (1-\omega)C_R$) .

## 2.3 Robotic setup

We used an anthropomorphic robotic arm (6DOF Kuka Agilus R6000) to hold the tray for this task. The tray which is used in this setup is a 70 cm by 70 cm square, and is attached to the end effector of the robotic arm. Two joints of the robotic arm were used as wrist joint and elbow joint to tilt the tray in two axes. A ball with a radius of 3cm is placed on the tray and an infrared camera system (OptiTrack) is deployed above the robotic arm which oversees the tray. The robotic setup is shown in Figure 2. The infrared camera output is used to capture and track the position and velocity of the ball in real-time with 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 find the position of the ball on the tray.

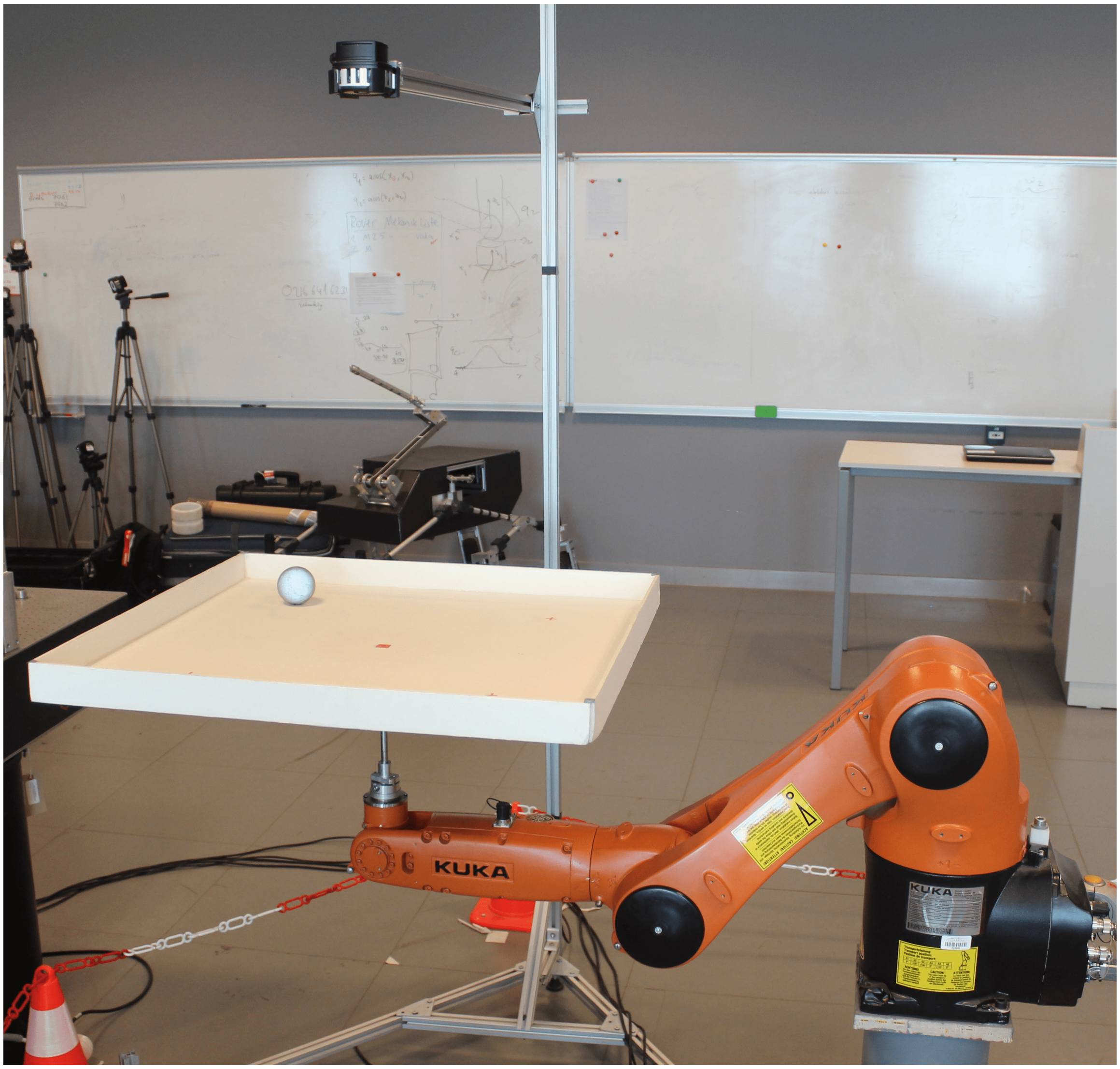


**Figure 2:** Robotic setup, The tray (70 cm by 70 cm) is held by the robotic arm, and the camera is placed on the top of the tray

### 2.3.1 Robot Teleoperation

In order for the human to teleoperate the Robotic arm to tilt the tray and perform the task, a standard computer mouse is used as a feed-forward interface. The human teleoperation commands are obtained with the movements of the computer mouse. The horizontal and vertical displacements of the mouse are linearly mapped as the desired angular movements of the wrist joint and elbow joint, respectively. This tilts the tray in two axes and moves the ball to the corresponding direction. The control frequency was 250Hz. The linear scale used to map mouse movements to robot movements was tuned experimentally to provide an intuitive teleoperation.

$\theta_{wrist-desired} = \theta_{wrist-current} + k\Delta x$

$\theta_{elbow-desired} = \theta_{elbow-current} + k\Delta y$

Here $\theta_{wrist}$ and $\theta_{elbow}$ denote joint angles of the robot, k (k = 1) is mouse scale constant and $\Delta x$ and $\Delta y$ are captured horizontal and vertical displacements of the mouse.

### 2.3.2 Human-Robot Shared Control

In the shared control condition both human and robot are involved in generating the control commands to accomplish the given task. The human starts performing the task, simultaneously the robot assists the human by inferring the human intention (see Section 2.3.3.1), taking share in control and augmenting the human control commands.

### 2.3.3 Autonomous Controller

The robot generates its commands by using an autonomous controller that moves and balances the ball on the predicted target position (obtained by a human intention inference method which is explained in the next Section 2.3.3.1). This autonomous controller is obtained by imitation learning. We defined the states of the task as follow:

$S = [x, y, V_x, V_y, J_{wrist}, J_{elbow}, \omega_{wrist}, \omega_{elbow}]$

Where $(x, y)$ and $(Vx, Vy)$ indicate ball position and ball velocity in x and y axis, respectively, and $(J_{wrist}, J_{elbow})$ are robot's joints angles, and $(\omega_{wrist}, \omega_{elbow})$ are the joint's angular velocities.

We assumed that control commands issued at the states experienced by the system are sufficient for successful task execution. For the ball balancing task, if we assume that the relation between the control commands and the state is linear, then the control policy can be approximated by linear regression. To obtain data for linear regression, an expert subject performed the task multiple times to balance the ball on the center of the tray, while task states and corresponding commands were being recorded. The recorded states and commands were collected in the rows of S (state matrix), C (commands matrix) respectively. With the linear relation assumption that $SW = C$, the weight matrix W that maps the states to the corresponding commands, can be found by:

$W = S^{+}C$ (Where $S^{+}$ is the pseudo inverse of $S$)

Once $W$ is found, having the current state(s), autonomous controller command(c), can be obtained by: $c = sW$ The predicted commands and actual commands of the expert subject are shown in Figure 3. 200 seconds of expert demonstration was used to obtain the policy for balancing the ball on the center of the tray with random starting positions. This was then used to construct a controller that can balance the ball anywhere on the tray by mapping the desired target point on the tray to the center of the tray which was the target position when the expert data was being collected.

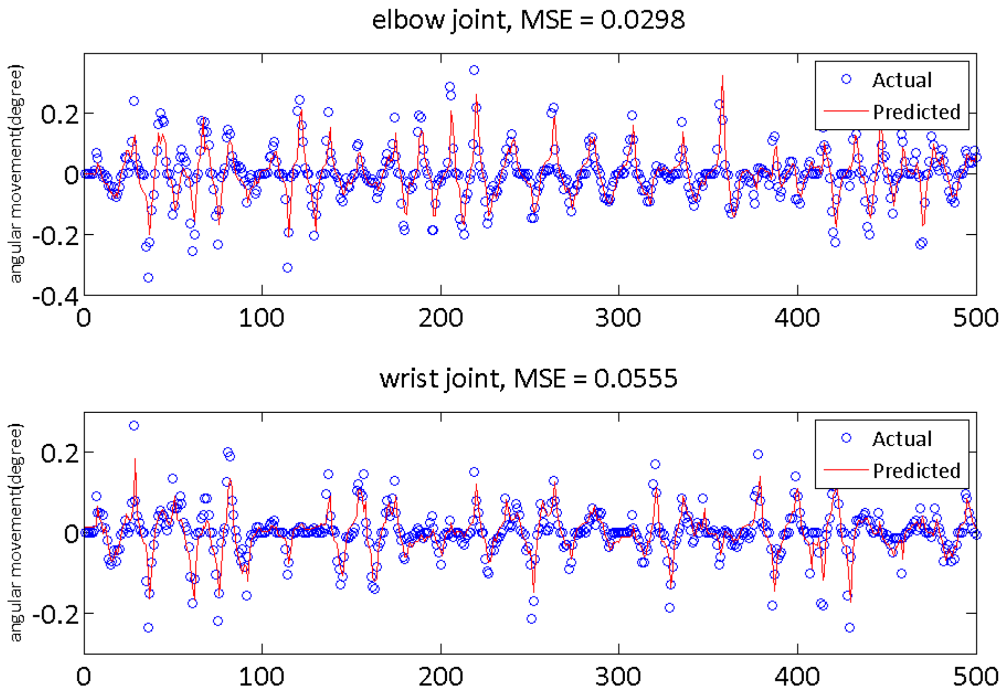


**Figure 3:** Linear regression error, actual commands and predicted commands obtained by linear regression for robot wrist joint and elbow joint. Only 500 data points (collected in 2 seconds) are shown for clarity, with MSE = 0.0298 for wrist and MSE = 0.0555 for elbow joint.

#### *2.3.3.1 Human Intention Inference*

Human intention in this experiment refers to the goal target position that the human tries to move and balance the ball on it. This Inference starts when 1000 data points (in 4 seconds) are collected after the human operator starts the ball balancing task. The ball positions in a moving window is used to estimate the goal of the human operator. This window includes 1000 data points which are collected in the past 4 seconds. The ball position distribution over the window is modeled as a Gaussian distribution, although other alternatives are possible.

$$P\begin{bmatrix} x \\ y \end{bmatrix} \sim N(\mu, \Sigma)$$

Where X and Y indicate the ball position in x and y axes. $\mu$ is the mean matrix defined as:

$$\mu = \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$$

Where $\mu_x$ and $\mu_y$ are the mean value of the ball position in x and y axes, $\Sigma$ is covariance matrix defined as:

$$\Sigma = \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy}. \end{bmatrix}$$

where $\Sigma_{xx} = var(x)$,$\Sigma_{yy} = var(y)$ and $\Sigma_{xy} = {\Sigma_{yx}}^T = cov(x, y)$

Consequently, the mean of the Gaussian function indicates the estimated goal position and the variance of that Gaussian function indicates the confidence of the estimate. It updates the inferred goal position based on the changes on the mean of the Gaussian function and this process continuous until the end of session (see Figure 4).

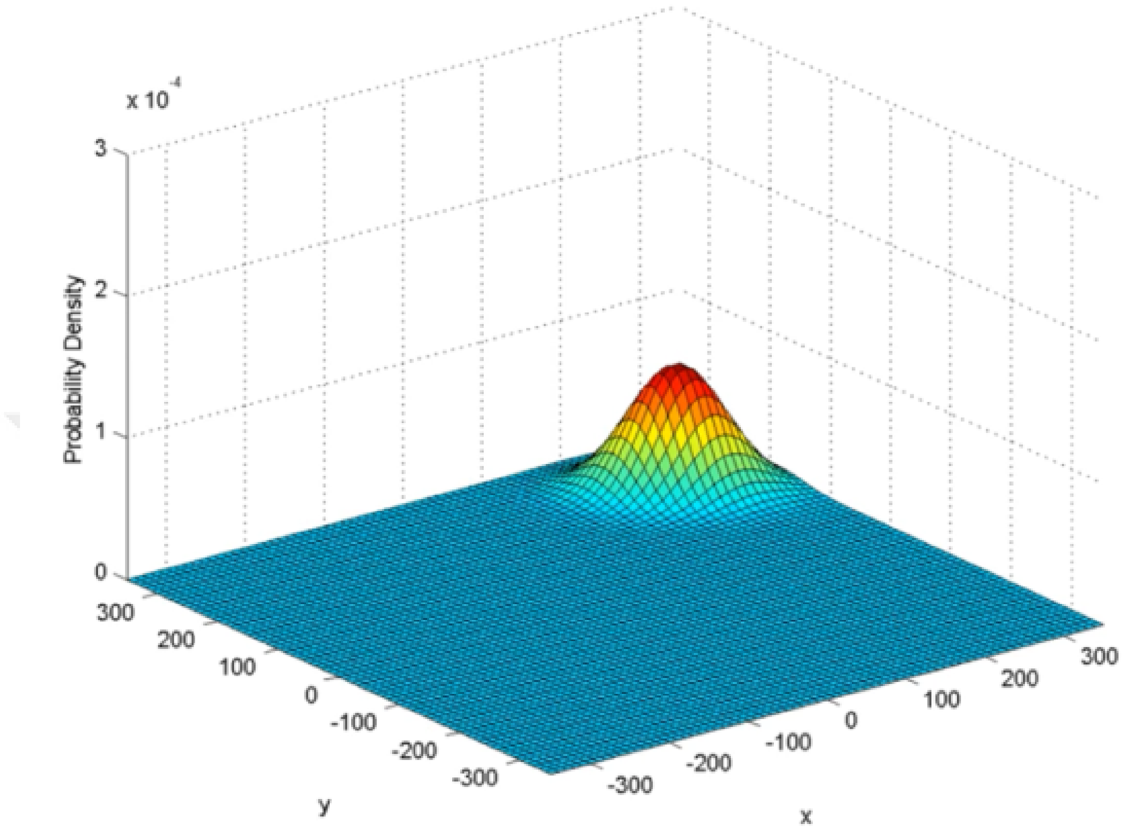


**Figure 4:** Human intention inference, the ball position distribution on the tray.

In phase 1 of the experiments a histogram based intention inference method was used in which the human goal position is set to the ball position histogram maximum point (see Figure 5). The goal position is updated with histogram changes, by using a time-windowed indicator. This method also sets the predicted goal position after a certain period of time passes (4 seconds) and enough data is recorded.

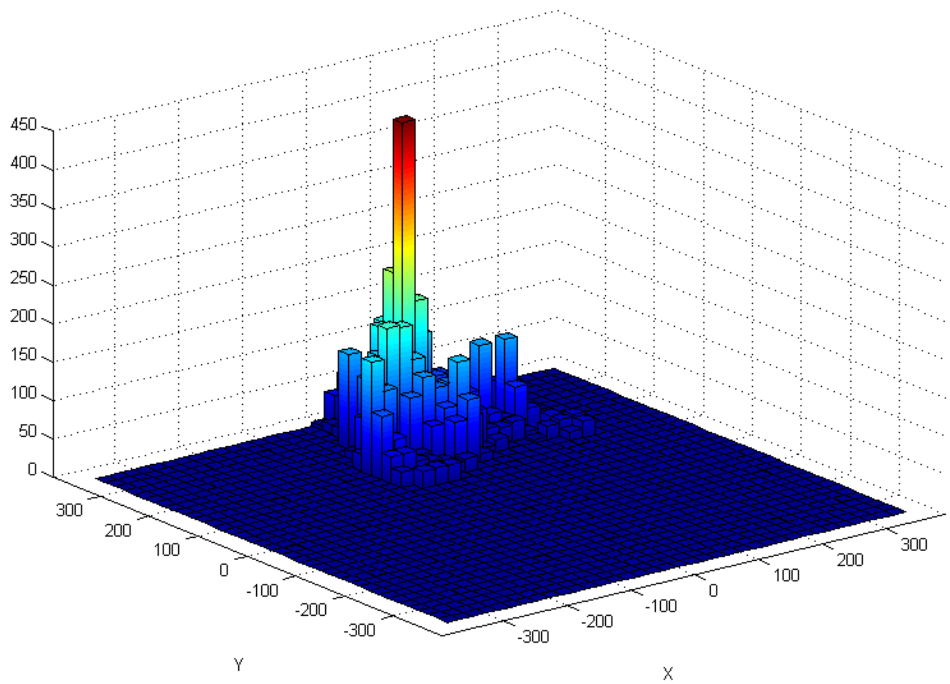


**Figure 5:** Human intention inference, the ball position histogram on the tray.

# Chapter III

# EXPERIMENTS AND RESULTS

## *3.1 Experiments - Phase 1*

In this phase we aimed to examine the efficiency of the proposed shared control frame work by comparing it to the performance of the robot and the human, for this purpose, experiments were conducted under three different conditions. 'Robot Control', 'Human Control' and 'Shared Control' for a set of target points selected on the tray.

**Robot Control Condition:** In autonomous robot control, only the autonomous controller generates the control commands.

**Human Control Condition:** In the human control condition only human teleoperation commands will drive the robot as it was explained in Section 2.3.1.

**Shared Control Condition:** In the shared control condition both human and robot are involved in generating the control commands to accomplish the given task. The human starts performing the task, simultaneously the robot assists the human by inferring the human intention, taking share in control and augmenting the human control commands. The final control command that drives the robot is a convex combination of the human and robot generated commands.

### 3.1.1 Participants

20 naive subjects (16 males and 4 females) were divided into 2 groups to perform the task in shared control condition and human control control to provide the first trial result.

### 3.1.2 Experiment Design

In this experiment ball was placed on the center of the tray in the beginning and each of the subjects had maximum two minutes to move and balance the ball on the target position to finish the task. In order an attempt to be successful the final ball position distance to the target position should not be more than 3 cm. This value is chosen because the ball radius is 3 cm.

### 3.1.3 Performance Measure

Two performance measures were defined for this experiment.

**Task completion time:** The time that the operator takes to balance the ball on the target position on the tray.

**Positional Error:** The distance of the final ball position to the target position.

### 3.1.4 Results

The result of this experiment showed that in the human control condition, five out of ten subjects failed to finish the task. In the autonomous robot control out of ten trials, two were unsuccessful, since the distance of the final position to the target position was out of acceptable range, due to surface irregularities. In shared control group, out of ten subjects only one subject failed to achieve the goal in the given time. We found five target points which could be achieved successfully in all the three conditions. We analyzed the performance for these five points, by using the defined performance measures.

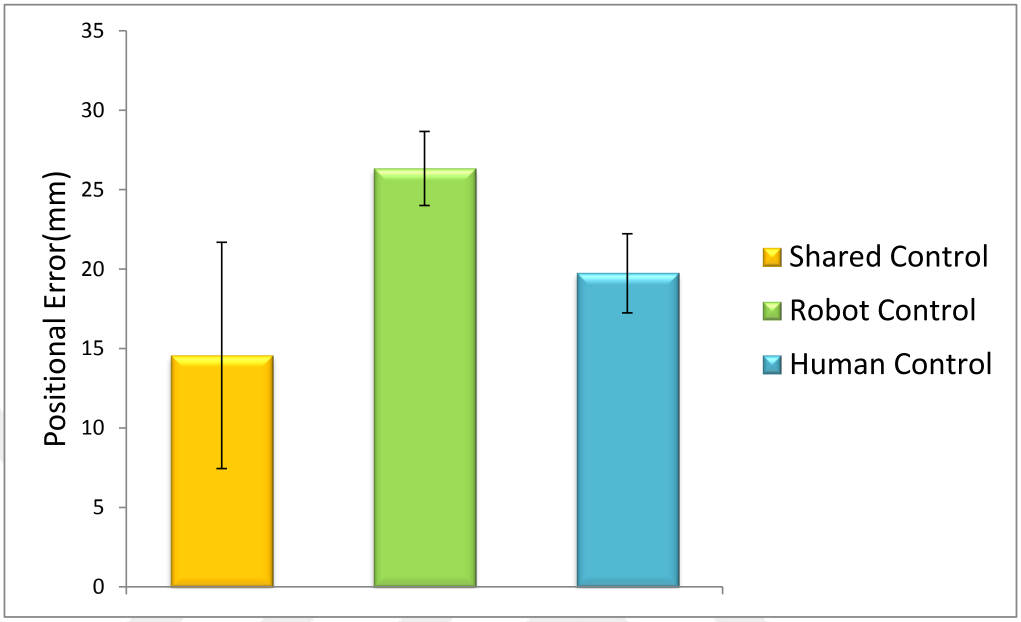


**Figure 6:** Shared Control vs Human Control vs Robot Control, positional error, mean of positional error for the 3 conditions, vertical error bars indicate standard deviation.

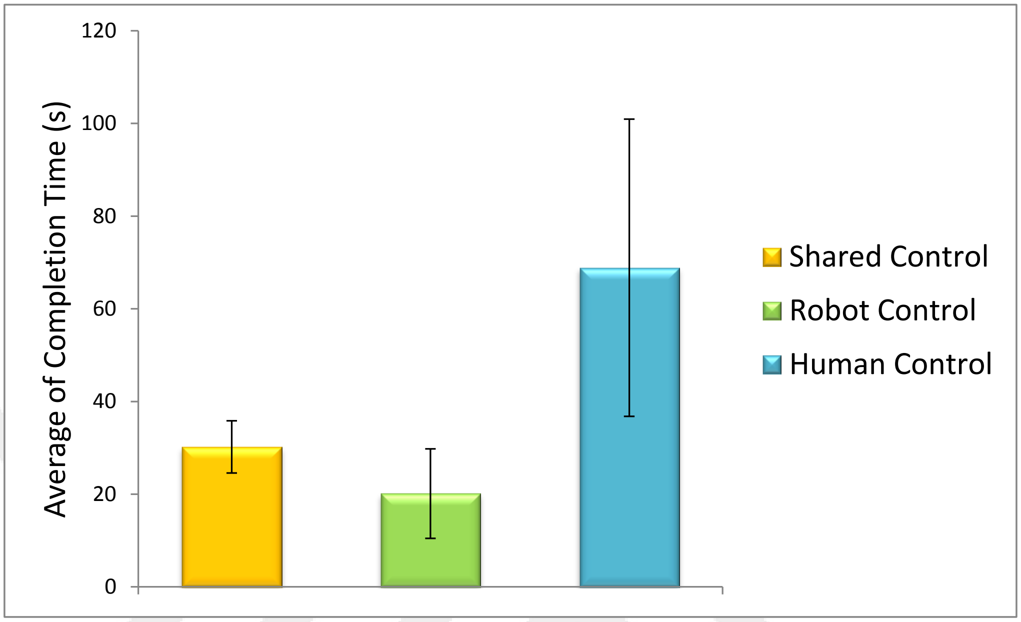


**Figure 7:** Shared Control vs Human Control vs Robot Control, completion time, mean of completion for the 3 conditions, vertical error bars indicate standard deviation.

According to completion time in Figure 7 and positional error in Figure 6, we can say that the robot control and shared control did not have significant difference in completion time according to T-Test analysis and both were better than human control (see Table 1) , however, shared control was significantly better than robot in positional accuracy (see Table 2). Considering both performance measures, shared control presents higher performance in comparison to the other two conditions, which is almost as fast as the robot and more accurate than both the robot and the human.

| | Shared Control | Robot Control |
|---|---|---|
| **Robot Control** | 0.108723 | - |
| **Human Control** | 0.041547 | 0.01948 |

**Table 1:** Shared Control vs Human Control vs Robot Control, completion time P-Value

| | Shared Control | Robot Control |
|---|---|---|
| **Robot Control** | 0.036668 | - |
| **Human Control** | 0.256616 | 0.0011847 |

**Table 2:** Shared Control vs Human Control vs Robot Control, positional error P-Value

## *3.2 Experiments - Phase 2*

To investigate if this framework can help the humans to learn faster and improve their skills more in comparison to the condition, where they perform the task alone, a set of experiments were conducted under two conditions, 'Human Control' and 'Shared Control'.

**Human Control Condition:** In the human control condition only human teleoperation commands will drive the robot as it was explained in Section 2.3.1.

**Shared Control Condition:** In the shared control condition both human and robot are involved in generating the control commands to accomplish the given task. The human starts performing the task, simultaneously the robot assists the human by inferring the human intention, taking share in control and augmenting the human control commands. The final control command that drives the robot is a convex combination of the human and robot generated commands. In this condition subject were not instructed about the role of the robot in control.

### 3.2.1 Participants

20 (12 males and 8 females) naive human subjects were volunteered to do the experiment. They were students of engineering and psychology faculties at Özyegin University in Turkey. They were chosen in pairs according to age and gender and divided into two groups to perform the task under human control and shared control conditions. In the human control condition 6 male and 4 female students with the mean age of 25.80 ranging 22 and 28 years participated. In the shared control condition 6 male and 4 female students with the mean age of 25.90 ranging 23 and 31 years participated.

### 3.2.2 Experiment Design

Four target positions with equal distance to the tray center were marked on the tray which served as possible targets for the subjects but the robot is not given the knowledge of these four targets. At the beginning of one experimental trial, the ball is positioned at the center of the tray with zero velocity and the subject tries to move and balance the ball on one of the four marked target positions on the tray. Each experimental session includes four sub-sessions (Blocks) and a sub-session is made of four experimental trials, thus one experimental session includes 16 trials. To not to tire the subjects, after each sub-session they could take a short break. For each subject, four experimental sessions were conducted in separate but consecutive days which makes 64 trials in total for each subject. The purpose of this was to keep track of their learning progress. 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 subjects. The subjects were not aware that which condition (human control or shared control) they are performing the task in, and the subjects in the shared control group did not know that the robot is also involved in the task. At the end of the last experimental session the subjects were asked to fill a questionnaire about demographic information.

### 3.2.3 Performance Measure

Three performance measures were defined for this experiment.

**Length of trajectory:**Length of trajectory is defined as the length of the path that the ball travels on the tray in one trial, starting from the tray center to the desired target point. Smaller length of trajectory presents a higher task performance.

**Task completion time:** The time that the operator takes to balance the ball on the target position on the tray.

**Positional error:** The distance of the final ball position to the target position.

### 3.2.4 Performance Results

In this section we are reporting and comparing the performance of subjects in human control and shared control condition.
To answer the research question that if there is any group mean difference in performance between shared control condition and human control condition we performed the following analysis.

#### *3.2.4.1 Trajectory Length Analysis*

We ran one-way MANOVA for four days' performances based on trajectory length. As can be seen in Table 3, there was no significant difference between shared control and human control conditions in subjects' trajectory length performances for the first and second days. However, there was a group mean difference for these two conditions in the third and fourth day that in the shared condition group mean of trajectory length performances was lower than the one on the human control condition ( see Table 3 and Figure 8).

| Days | Condition | Mean(mm) | Std. Deviation(mm) | ANOVA |
|---|---|---|---|---|
| day1 | Shared control | 6138.8013 | 4003.30099 | $F(1,18)=.005$, $p=.943$, eta$^2$=.000 |
| | Human control | 6238.4168 | 1711.29810 | |
| day2 | Shared control | 3450.5946 | 2028.87085 | $F(1,18)=.2.171$, $p=.158$, eta$^2$=.108 |
| | Human control | 5005.7661 | 2650.08196 | |
| **day3** | **Shared control** | **2298.1561** | **1057.63405** | **$F(1,18)=6.248$, $p=.022$, eta$^2$=.258** |
| | **Human control** | **3908.4740** | **1741.27786** | |
| **day4** | **Shared control** | **1733.2929** | **623.72900** | **$F(1,18)=13.193$, $p=.002$, eta$^2$=.423** |
| | **Human control** | **3894.1631** | **1774.92222** | |
| **Wilks' Lambda=.500, $F(4, 15)=3.75$, $p$=026, eta$^2$=.50** | | | | |

**Table 3:** Shared Control vs Human Control, performance analysis - trajectory length: means, standard deviations, and MANOVA for day 1, day 2, day 3, and day 4 performance of human control and shared control Conditions.

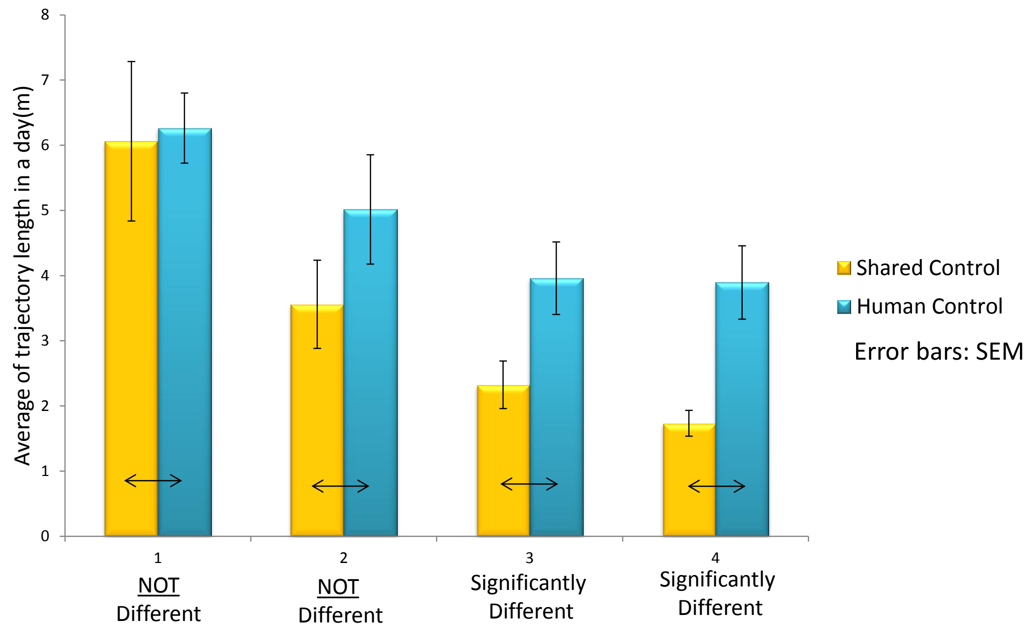


**Figure 8:** Shared Control vs Human Control, daily performance - trajectory length, means and standard error of the mean for day1, day2, day3, and day4 performance of human control and shared control conditions.

To find if the performance was the same in shared control and human control in the first day, we run one-way MANOVA to answer this research question. Results showed that although MANOVA was significant but follow-up ANOVAs for each block was not significant (see Table 4). This means that there was no significant difference between shared control group mean and human control group mean in trajectory length performances for none of four blocks in the first day.

| Blocks | Condition | Mean(mm) | Std. Deviation(mm) | ANOVA |
|---|---|---|---|---|
| block1 | Shared control | 9707.7720 | 6441.76467 | $F(1,18)=.443$, $p=.514$, $eta^2=.024$ |
| | Human control | 8280.4345 | 2124.37341 | |
| block2 | Shared control | 5282.1938 | 4072.19952 | $F(1,18)=1.992$, $p=.175$, $eta^2=.100$ |
| | Human control | 7439.6495 | 2603.86839 | |
| block3 | Shared control | 5026.2789 | 3407.24118 | $F(1,18)=.119$, $p=.734$, $eta^2=.007$ |
| | Human control | 5487.1458 | 2505.34289 | |
| block4 | Shared control | 4538.9603 | 3459.35288 | $F(1,18)=.394$, $p=.538$, $eta^2=.021$ |
| | Human control | 3746.4376 | 1997.00525 | |
| **Wilks' Lambda=.496, $F(4, 15)=3.81$, $p$=025, $eta^2=.504$** | | | | |

**Table 4:** Shared Control vs Human Control on the first day, trajectory length, performance analysis on the first day: means, standard deviations, and MANOVA for block1, block 2, block 3, and block 4 performance of human control and shared control performance for the day 1.

Is there any difference in trajectory length performance between days for shared control condition and human control condition separately for the four days of experiment? To test this research question Finally to track the progress in days inside of these two conditions, we ran several paired-samples T-Test for shared control and human control conditions separately. As can be seen in Table 5 and Figure 9, in the shared control condition trajectory length performance in each day was significantly different from each other for four days with getting lower day by day from day1 to day4.

| | | Mean | Std. Deviation | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|
| Pair 1 | day1 | 6138.8013 | 4003.30099 | **2.798** | **9** | **.021** |
| | day2 | 3450.5946 | 2028.87085 | | | |
| Pair 2 | day1 | 6138.8013 | 4003.30099 | **3.719** | **9** | **.005** |
| | day3 | 2298.1561 | 1057.63405 | | | |
| Pair 3 | day1 | 6138.8013 | 4003.30099 | **3.741** | **9** | **.005** |
| | day4 | 1733.2929 | 623.72900 | | | |
| Pair 4 | day2 | 3450.5946 | 2028.87085 | **2.876** | **9** | **.018** |
| | day3 | 2298.1561 | 1057.63405 | | | |
| Pair 5 | day2 | 3450.5946 | 2028.87085 | **3.119** | **9** | **.012** |
| | day4 | 1733.2929 | 623.72900 | | | |
| Pair 6 | day3 | 2298.1561 | 1057.63405 | **3.119** | **9** | **.012** |
| | day4 | 1733.2929 | 623.72900 | | | |

**Table 5:** daily progress in Shared Control condition, trajectory length, means, standard deviations, and paired-samples T-Test for comparisons of day1 to day2, day1 to day3, day1 to day4, day2 to day3, day2 to day4 and day3 to day4 performances in shared control condition.

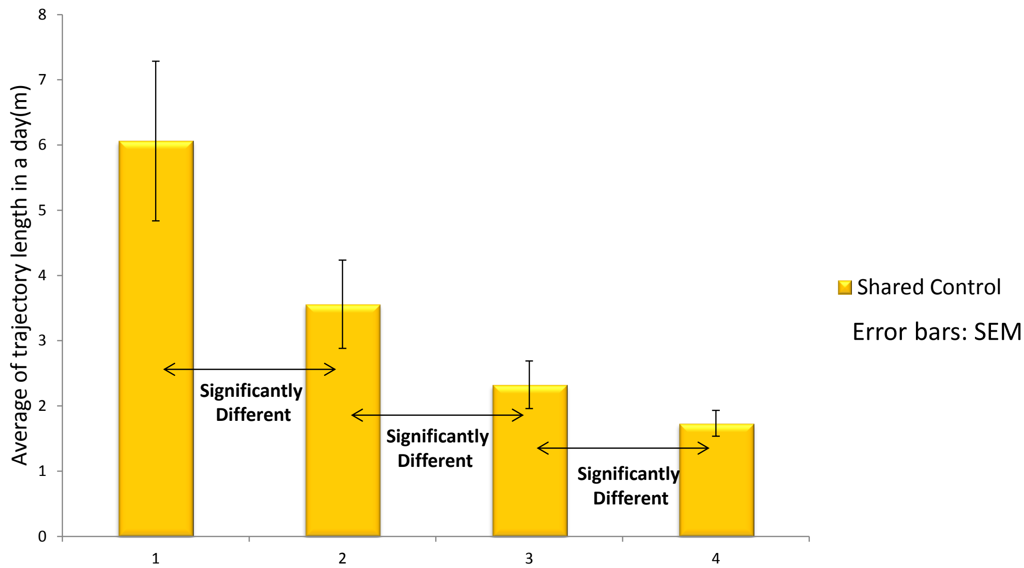


**Figure 9:** Shared Control daily performance, trajectory length, means and standard error of the mean for day1, day2, day3, and day4 performance of shared control condition.

Additionally, as can be seen in Table 6 and Figure 10 in human control condition trajectory length performance in each day was significantly different from day1 to day2, day1 to day3, day1 to day4, day2 to day3, day 2 to day4 with getting lower day by day from day1 to day3, but not from day 3 to day4.

| | | Mean(mm) | Std. Deviation(mm) | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|
| Pair 1 | day1 | 6238.4168 | 1711.29810 | 2.254 | 9 | .051 |
| | day2 | 5005.7661 | 2650.08196 | | | |
| Pair 2 | day1 | 6238.4168 | 1711.29810 | 4.373 | 9 | .002 |
| | day3 | 3908.4740 | 1741.27786 | | | |
| Pair 3 | day1 | 6238.4168 | 1711.29810 | 5.418 | 9 | .000 |
| | day4 | 3894.1631 | 1774.92222 | | | |
| Pair 4 | day2 | 5005.7661 | 2650.08196 | 2.515 | 9 | .033 |
| | day3 | 3908.4740 | 1741.27786 | | | |
| Pair 5 | day2 | 5005.7661 | 2650.08196 | 2.328 | 9 | .045 |
| | day4 | 3894.1631 | 1774.92222 | | | |
| Pair 6 | day3 | 3908.4740 | 1741.27786 | .060 | 9 | .953 |
| | day4 | 3894.1631 | 1774.92222 | | | |

**Table 6:** Daily progress in Human Control condition, trajectory length, means, standard deviations, and paired-samples T-Test for comparisons of day1 to day2, day1 to day3, day1 to day4, day2 to day3, day2 to day4 and day3 to day4 performances in human control condition.

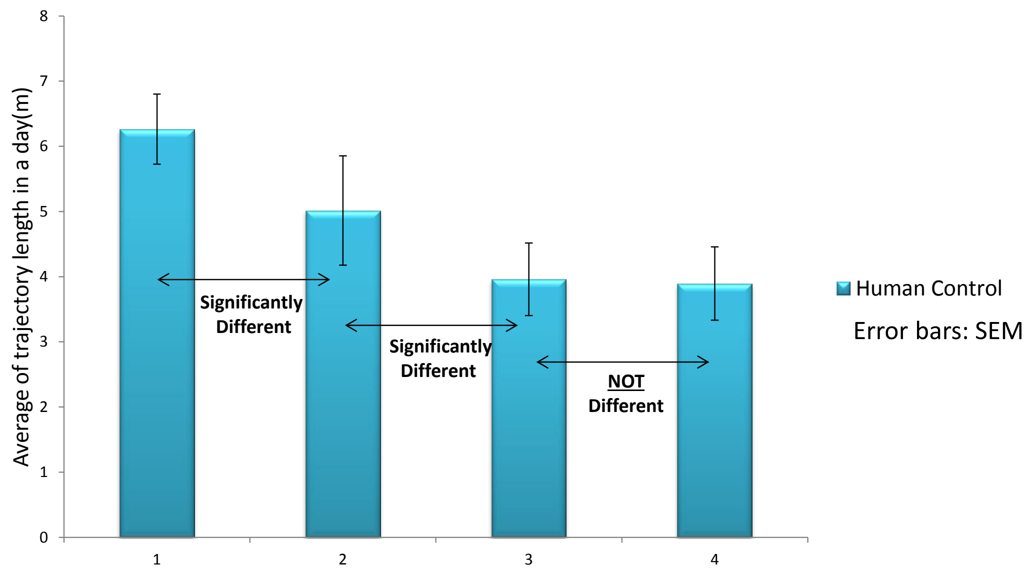


**Figure 10:** Human Control daily performance, trajectory length, means and standard error of the mean for day1, day2, day3, and day4 performance of human control condition.

We can say that the task performance in human control condition, was approximately the same in day 3 and day 4 and they did not have significant progress from day 3 to day 4 which suggests that the learning stopped at the day 3, while in shared control group there was still a significant progress from day 3 to day 4.

*3.2.4.2 Ball movement trajectory analysis*

Here progress in ball movement trajectory is reported and compared for 5 subjects in Human control condition and 5 subjects in Shared control condition. We picked the third trial for one target in 4 consecutive days as a sample to show how did they perform in two different conditions in Figure 11 and Figure 12 .

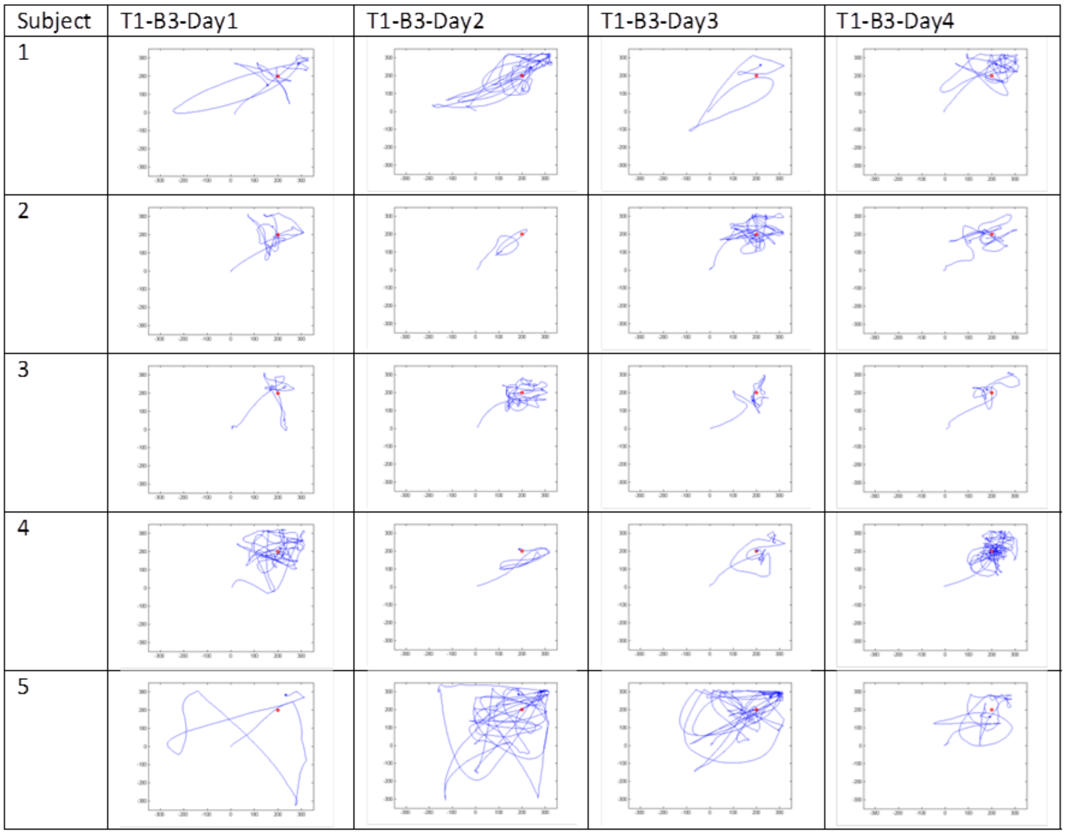


**Figure 11:** Ball movement trajectory in Human Control condition. The third trial for one target in 4 consecutive days is picked as a sample.

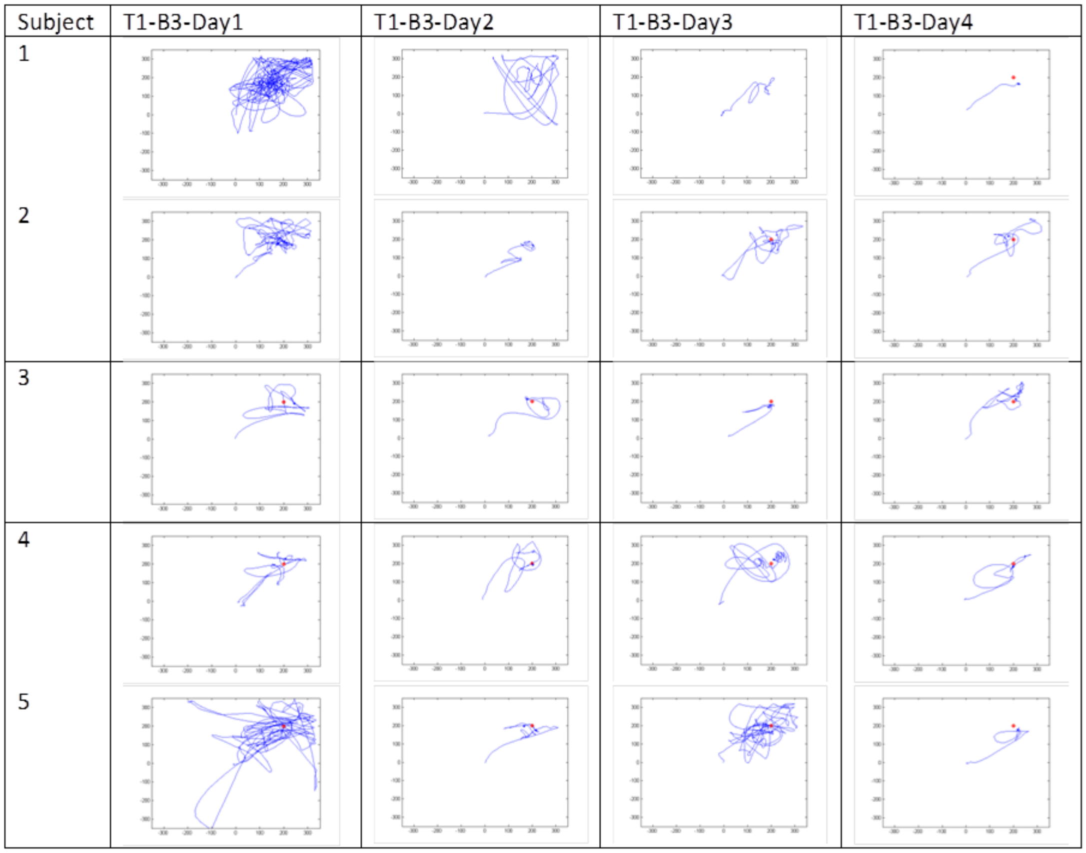


**Figure 12:** Ball movement trajectory in Shared Control condition. The third trial for one target in 4 consecutive days is picked as a sample

As we can observe in Figure 11 and Figure 12 some subjects in shared control condition show high exploration in the beginning that could allow them to observe and learn the robot strategy better and react accordingly as well, which led to a better collaboration and achieving a more straight forward trajectory to the target at the end.

#### *3.2.4.3 Completion Time Analysis*

Performance of shared control and human control condition based on their task completion time is shown in Figure 13. We performed T-Test analysis (shown in Table 7) to investigate if there is a significant difference in performance based on their completion time.

| Completion Time | | | | |
|---|---|---|---|---|
| Days | Condition | Mean(s) | Standard Deviation(s) | T.Test |
| Day1 | Shared Control | 66.6131276 | 26.45366794 | *p= 0.506* |
| | Human Control | 73.2033094 | 12.25128027 | |
| Day2 | Shared Control | 50.1727592 | 20.98163457 | *p=0.267* |
| | Human Control | 60.3783606 | 16.58844836 | |
| Day3 | Shared Control | 44.8091715 | 21.34932033 | *p=0.380* |
| | Human Control | 52.5254526 | 14.37773842 | |
| **Day4** | **Shared Control** | **33.4996614** | **13.79181896** | ***p=0.045*** |
| | **Human Control** | **48.8763027** | **16.51002067** | |
| **T.Test, two tailed, two sample unequal variances** | | | | |

**Table 7:** Shared Control vs Human Control, performance analysis, completion time: Means, standard deviations, and T-Test for day 1, day 2, day 3, and day 4 performance of human control and shared control conditions.

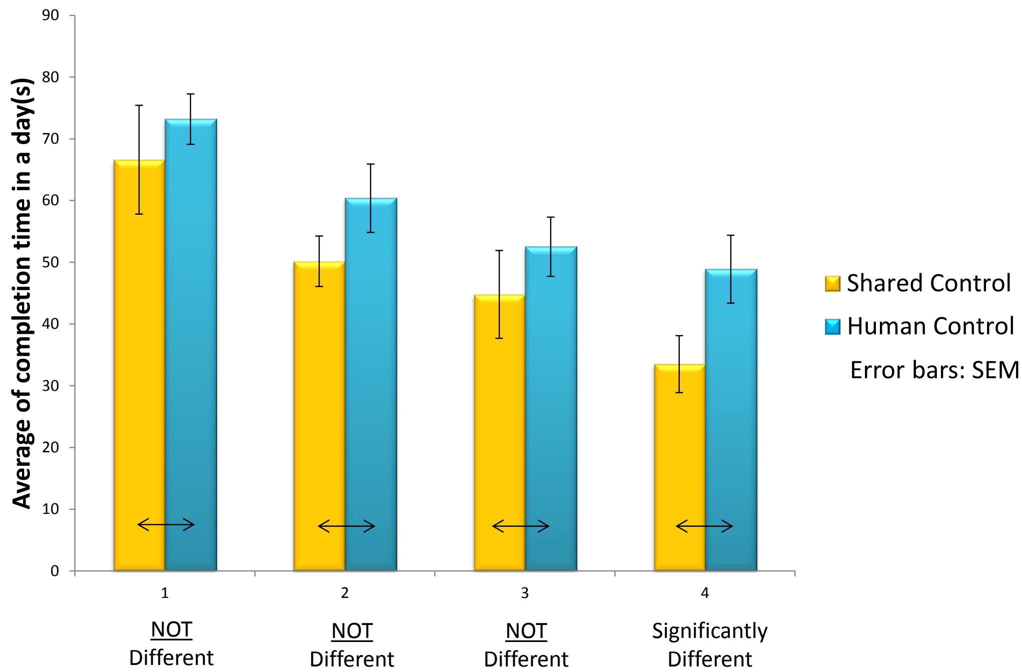


**Figure 13:** Shared Control vs Human Control, daily performance, completion time, means and standard error of the mean for day1, day2, day3, and day4 performance of human control and shared control conditions.

As it can be seen in Figure 13 and Table 7, although there was not a significant difference in day1, day2 and day3 between shared control and human control condition, shared control performance was better than human control condition with less completion time in all the days of experiment, while in the fourth day of experiment the performance of shared control condition becomes significantly better than human control condition.

#### *3.2.4.4 Positional Error Analysis*

Daily means of positional error in shared control and human control conditions are reported in Figure 14. T-Test analysis was also performed to compare their performance between the two conditions based on positional error (shown in Table 8).

| Positional Error | | | | |
|---|---|---|---|---|
| Days | Condition | Mean(mm) | Standard Deviation(mm) | T.Test |
| Day1 | Shared Control | 54.373508 | 29.07634881 | *p= 0.243* |
| | Human Control | 62.56614 | 18.70366375 | |
| Day2 | Shared Control | 47.669623 | 22.2203969 | *p=0.402* |
| | Human Control | 55.793491 | 17.6928106 | |
| Day3 | Shared Control | 43.704052 | 23.10421683 | *p=0.192* |
| | Human Control | 56.888316 | 17.9212144 | |
| Day4 | Shared Control | 32.85529 | 11.13075083 | *p=0.130* |
| | Human Control | 44.565074 | 19.15738838 | |
| **T.Test, two tailed, two sample unequal variances** | | | | |

**Table 8:** Shared Control vs Human Control, performance analysis, positional error: means, standard deviations, and T-Test for day 1, day 2, day 3, and day 4 performance of human control and shared control Conditions.

Although we could not find a significant difference in shared control and human control daily performance based on their positional error, it can be seen in Figure 14, that in shared control condition, positional error decreased day by day and was always less than human control condition.

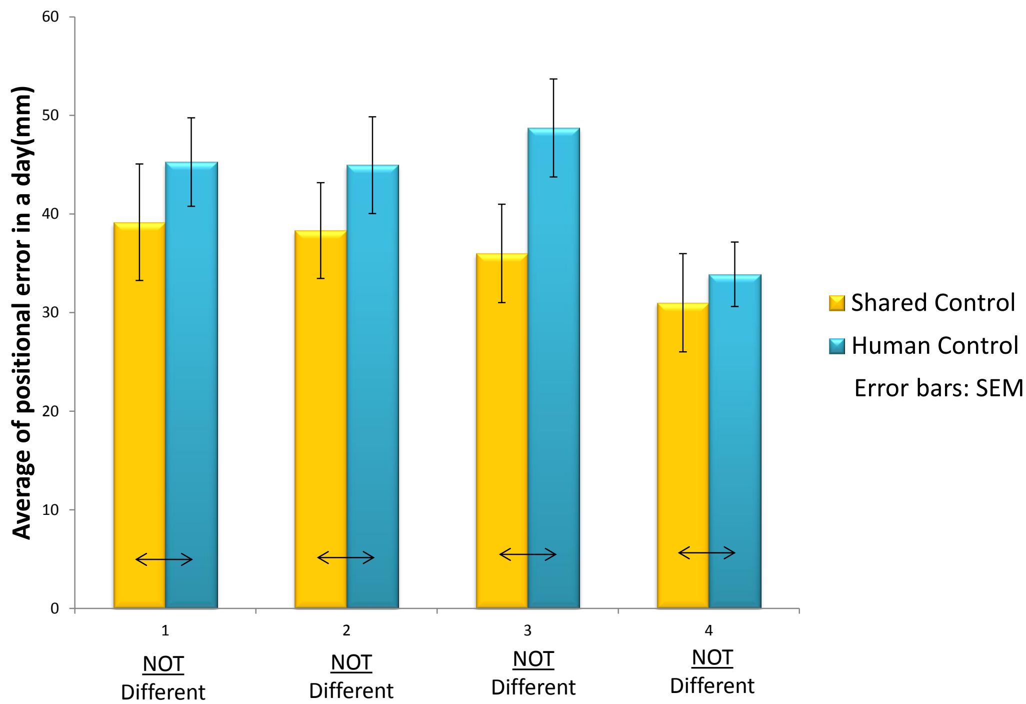


**Figure 14:** Shared Control vs Human Control, daily performance, positional error, means and standard error of the mean for day1, day2, day3, and day4 performance of human control and shared control conditions.

### 3.2.5 Learning Progress Results

In this section we are exploring the learning progress of individual subjects and compare them between the human control condition and shared control condition, to understand how fast they adapt to the system and learn the designed task. To track subjects learning progress during the experiment, we found the trend of their performance in the experiment based on trajectory length. To find the fit that explains the data trend the best, we examined fitting Linear, Exponential, and Power function over the data in all the 64 trials for each subject and reported the R-Squared value.

| Condition | Subject | R-Squared 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 | p |
| | 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 |
| | Subject 10 | 0.2196 | 0.2254 | 0.2723 | p |
| Human Control | Subject 11 | 0.016 | 0.0069 | 0.0527 | p |
| | Subject 12 | 0.1343 | 0.1593 | 0.1908 | p |
| | Subject 13 | 0.0939 | 0.0391 | 0.1424 | p |
| | Subject 14 | 0.2052 | 0.1065 | 0.1101 | l |
| | Subject 15 | 0.1267 | 0.0905 | 0.0946 | l |
| | Subject 16 | 0.002 | 0.00008 | 0.006 | p |
| | Subject 17 | 0.133 | 0.1747 | 0.1606 | e |
| | Subject 18 | 0.0048 | 0.0017 | 0.0005 | l |
| | Subject 19 | 0.1885 | 0.1656 | 0.2259 | p |
| | Subject 20 | 0.0495 | 0.0172 | 0.0238 | l |
| **Average** | | **0.16518** | **0.165094** | **0.19021** | **p** |

**Table 9:** R-Squared value of the fitted regression functions.

The fitted Power function resulted in highest R-Squared value for all the subjects in both human control and shared control on average, see Table 9, thus was chosen as the trend of the learning progress in this experiment. The fitted power functions for all the subjects are shown in Figure 15, and Figure 16.

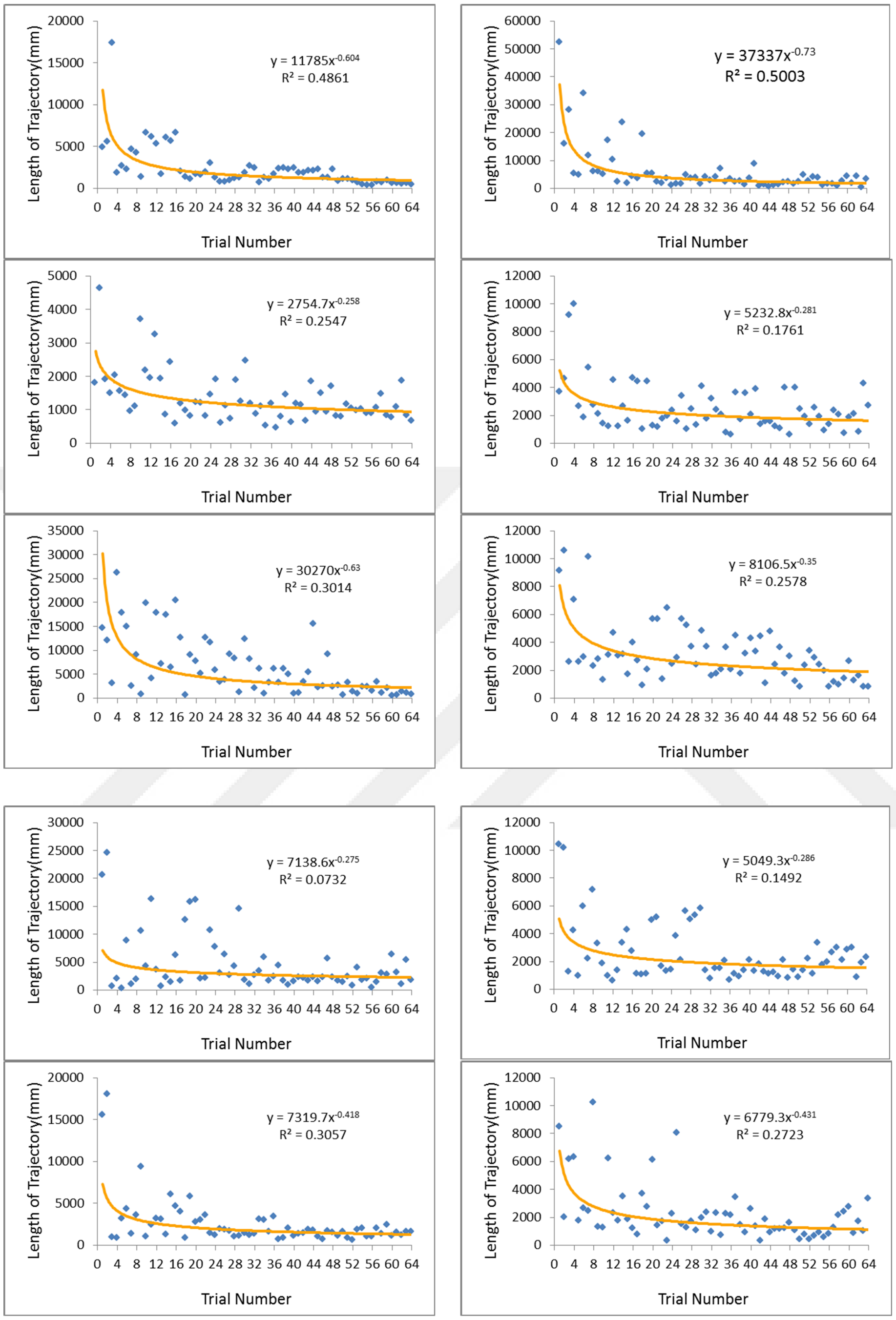


**Figure 15:** Fitted power function on the performance of shared control condition

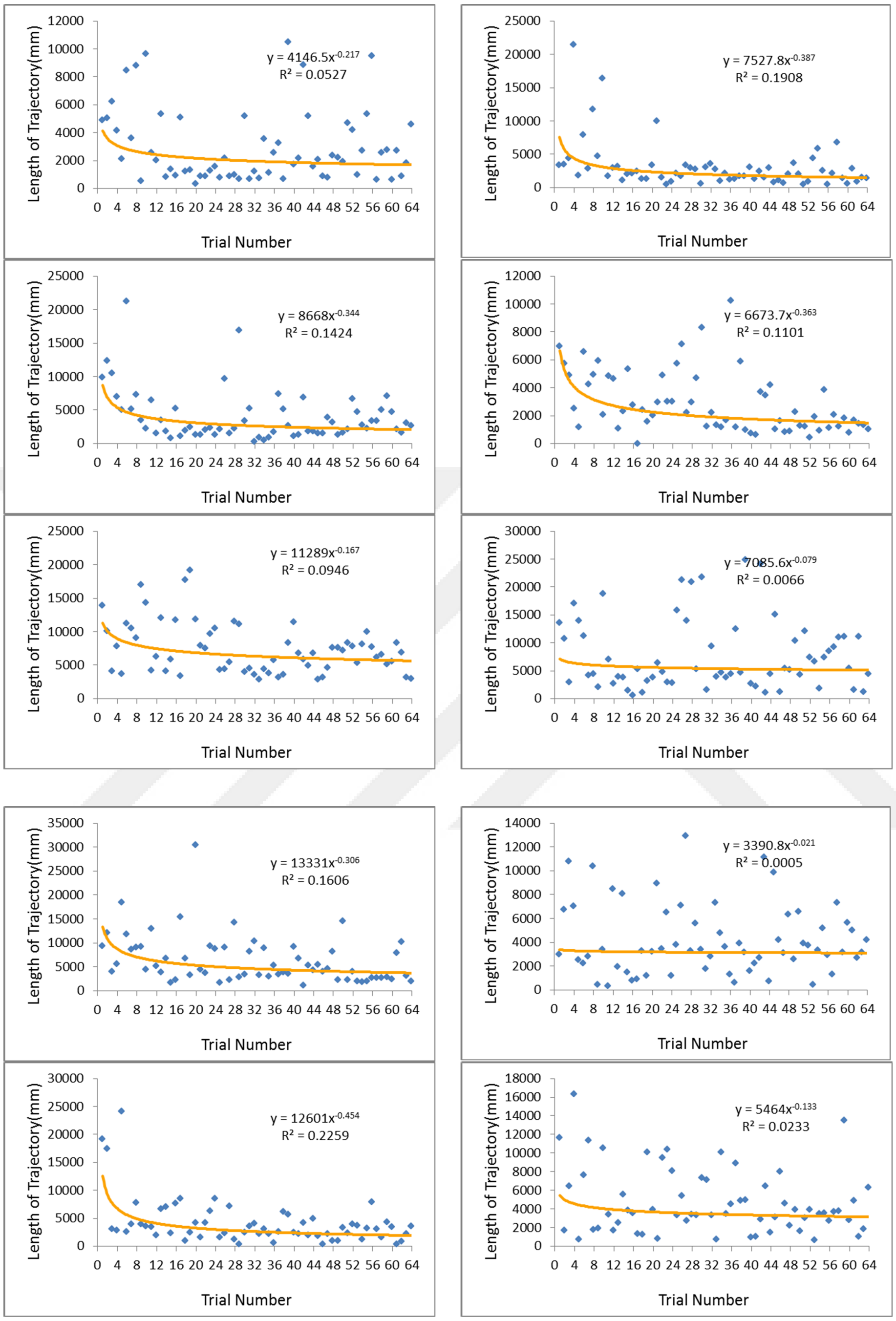


**Figure 16:** Fitted power function on the performance of human control condition

### 3.2.6 Learning Rate

We defined the additive inverse of **power** ( when $y = ax^{\mathbf{power}}$ ) as the learning rate parameter for each subject. The learning rate values are reported in the Table 10.

| Shared Control | | Human Control | |
|---|---|---|---|
| **Subject** | **Learning rate** | **Subject** | **Learning rate** |
| Subject 1 | 0.604 | Subject 11 | 0.217 |
| Subject 2 | 0.73 | Subject 12 | 0.387 |
| Subject 3 | 0.258 | Subject 13 | 0.344 |
| Subject 4 | 0.281 | Subject 14 | 0.363 |
| Subject 5 | 0.63 | Subject 15 | 0.167 |
| Subject 6 | 0.35 | Subject 16 | 0.079 |
| Subject 7 | 0.275 | Subject 17 | 0.306 |
| Subject 8 | 0.286 | Subject 18 | 0.021 |
| Subject 9 | 0.418 | Subject 19 | 0.454 |
| Subject 10 | 0.431 | Subject 20 | 0.133 |
| **Average** | **0.4263** | **Average** | **0.2471** |

**Table 10:** Learning rate of the subjects in human control and shared control condition

The subjects in shared control condition had a higher learning rate in compare to the subject in human control condition as it is shown in Table 10 and Figure 17.

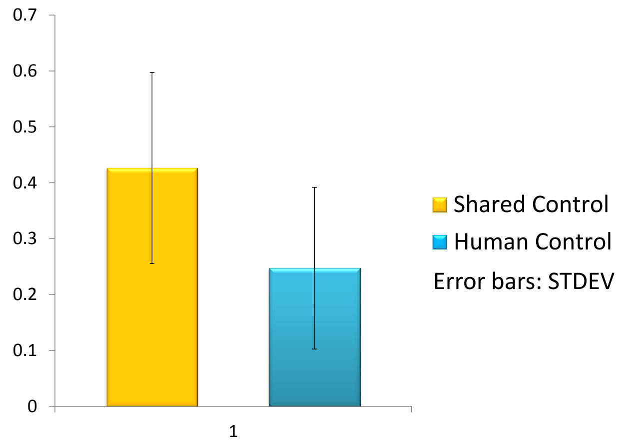


**Figure 17:** Mean of learning rate for shared control condition and human control condition, error bars are the standard error of the mean.

We performed T-Test analysis on the obtained learning rate between shared control and human control condition to inspect if the two populations are significantly different, see Table 11.

| | *Shared Control* | *Human Control* | diff | 95% Confidence Interval | |
|---|---|---|---|---|---|
| Mean | 0.4263 | 0.2471 | 0.179 | 0.030 | 0.329 |
| Variance | 0.029248 | 0.020932 | | | |
| Observations | 10 | 10 | | | |
| Hypothesized Mean Difference | 0 | | | | |
| df | 17 | | | | |
| t Stat | 2.530 | | | | |
| P(T<=t) two-tail | 0.022 | | Reject Null Hypothesis because p < 0.05 (Means are Different) | | |
| T Critical Two-tail | 2.110 | | | | |

**Table 11:** T-Test analysis on the learning rates between shared control condition and human control condition.

T-test results showed that the learning rates are significantly different in between the two shared control and human control conditions.

### 3.2.7 Survey Questionnaire

A survey questionnaire was given to subjects at the end of last experimental session to assess their experience while using the system. It should be mentioned that the subjects were not instructed about the role of the robot in the shared control condition. The questionnaire can be seen in Figure 18. The given answers to this questions by the subjects are attached in the appendix.

1 - How did you find the task involved in the experiment in the first days?

a) Very Hard b) Hard c) Neutral c) Easy d) Very Easy

2 - How did you find the task involved in the experiment in the last days?

a) Very Hard b) Hard c) Neutral c) Easy d) Very Easy

3 – How do you feel about your task performance?

a) I did not feel improvement a) Slowly I got better b) Suddenly I got better d) I don't know

4 – Were you comfortable while doing the task in the first days?

a) Very uncomfortable b) Uncomfortable c) Neutral c) Comfortable d) Very comfortable

5 – Were you comfortable while doing the task in at the last days?

a) Very uncomfortable b) Uncomfortable c) Neutral c) Comfortable d) Very comfortable

6 – Did you face any difficulty or problem while doing the task? If yes please explain.

7 – Did you get bored while doing the task? If yes when did it get boring? (Please write free text)

8 – Did you get tied while doing the task? If yes when did you get tired? (Please write free text)

9 – Do you think you have become an expert in this task? (Please write free text)

10 – Do you think the robot helped you or blocked you doing your task? (Please write free text)

**Figure 18:** Experiment questionnaire

We converted the verbal answers to question 10 to three classes negative (blocking), neutral(no help) and positive(helping) to learn their opinion about robot role in the task According to this, 9 out of 10 subjects in the shared control group had realized the robot participation, and 8 of those 9 subjects had found it helpful, and only one subject had found it blocking while trying to move fast and doing sudden actions. In the human control conditions 9 out of 10 subjects reported neutral as expected.

# Chapter IV

# CONCLUSION

## *4.1 Conclusion*

We introduced a synergistic human-robot collaboration system with human intention inference and investigated its effect on task execution and human learning progress by implementing it on a designed 'ball balancing' task in which a tray is held by an anthropomorphic robot arm and a ball is placed on the tray. The goal of this task is to move and balance the ball on a target position on the tray by controlling the robotic arm joints via an interface.

In the first phase of this study, Three control condition scenarios were considered for this task: full autonomous controller, where only the robot generates control commands named as 'Robot Control'; a human-in-the-loop controller named as 'Human Control', where the robot does not interfere with the control and a human-robot shared controller, named as 'Shared Control' in which the human starts performing the task while the robot attempts to predict the human intention and then take share in control to assist the human by augmenting the human control commands. For this purpose, since pursuing a common goal is necessary for a successful collaboration, a human intention prediction mechanism based on ball position histogram on the tray was developed to be used by the robot, The effectiveness of the proposed framework was examined by comparing the performance of shared controller with the other two control conditions (Human Control and Robot Control) based on two performance measures, namely task completion time and positional error. 10 naive subjects were employed for each condition (in total 20 subjects), to measure the task execution performance of naive solo operators and naive human-robot teams. According to this comparison, the human-robot shared control condition appears to be the best. The result suggests that our proposed shared control system can take advantage of the individual skills so as to cover their weakness.

In the second phase of experiments, we were interested to know how the human is influenced when interacts with machine autonomy, whether or not this collaboration can aid the human to improve and learn the task faster while interacting with a robot as a teammate. Two control scenarios were considered for the same task: Human Control condition and Shared Control condition. The intention inference mechanism was developed to a Gaussian estimation method to be used by the robot to estimate the human intention. To explore the human learning progress and adaptation to the system while collaborating with robot and solo, the designed task was performed by the human subjects in both conditions multiple times in consecutive days. The length of ball trajectory, completion time and positional error on the tray were chosen as the performance measure. 20 naive subjects were volunteered for this experiment. Each subject had 64 trials in four consecutive days to perform the ball balancing task. To track the subjects learning progress, we found the trend of their performance and measured their learning rate by fitting a power line on their trajectory length performance measure of all their 64 trials. The learning rate comparison between Human Control and Shared Control condition suggests that the human can learn the task and adapt to the system faster when collaborating with an assistive robot while granting a higher task performance, which allow us to say, this shared control framework can yield a higher task execution performance by taking advantage of human and robot individual capabilities and covering their weaknesses and also give the opportunity to humans to learn faster and improve themselves more than it was possible when performing the task alone.

## 4.2 Discussion

In a collaboration system for task execution the issue of who should be in control, when and how much, can be decided based on the task properties and the skills of shared control parties (humans and robots). For example in some settings where a human is expert in one part and the robot is specialized in another part of the task then a continuous weighted shared control may not be suitable, instead a switching shared control can be used which switches the control fully from the human to robot and from the robot to human. In other cases human may tune the weight share parameter manually, get more help from the robot in a specific situation or be himself/herself more or fully in control when needed. Adaptive weight sharing between human and robot where weight share can be changed autonomously based on both human and robot behavior, should be investigated. We performed some preliminary experiments in which we tuned the robot's share in control according to its confidence in the estimated human intention (see Section 2.3.3.1). We observed that this type of adaptive weight sharing has high potential for better human-robot collaborative systems, which should be further investigated.

When mixing, switching or generally sharing the control, the human and robot both get the opportunity to learn the other party's behavior and strategy. As in our experiment the humans could observe and understand the robot behavior by exploration in the beginning and achieve a higher performance more than they could achieve without sharing the control with robot. In this work, the robot already knew how to perform the task and its skills was fixed, however in a more general form of collaboration both human and robot try to learn the task and progress together, and their control share shall be combined. This simultaneous learning system is a more complex collaboration system which needs to be studied.

For this designed ball balancing task, although the Gaussian distribution assumption for inferring human intention was good enough, is probably not the best, other distributions might be more informative or accurate for inferring human intention in this task. More general frameworks such as inverse reinforcement learning that are applicable to any task can be used for human intention inference.

# Appendix

**CONSENT TO ACT AS A PARTICIPANT IN A RESEARCH STUDY**

TITLE: Human-robot shared control in the 'ball balancing task'

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SOURCE OF SUPPORT: Converge (Convergent Human Learning for Robot Skill Generation) Project supported by the European Commission FP7 MC-CIG under the grant agreement no 321700

***Why is this research being done?***

The objective of our research is to assess the efficacy of our human-robot shared control system in the 'ball balancing task'.

***Who is being asked to take part in this research study?***

Approximately 20 adults will be invited to participate in this study.

***What are the procedures of this study?***

You will be asked to take part in an experiment at the Robotics lab at EF513 Engineering Faculty. You will control a robotic arm using a computer mouse to perform a ball balancing task. Your mouse movements will be mapped to robot movements in real-time. Robot will be holding a tray which contains a ball that needs to be rolled and stopped at desired locations. An experiment session will take about 90 minutes. There will be 4 experimental sessions which will be conducted in separate but consecutive days. Measures relating to behavior and task performance will be collected. Demographic information, questionnaires (including personality traits, cultural characteristics, trust attitude in automation, and perceived workload) will be collected.

***How will my eligibility for the study be determined?***

1. College student or graduate, at least 18 years of age.
2. Turkish or English speaker

***What are the possible risks, side effects, and discomforts of this research study?***

**Figure 19:** The consent form which was given to the participants before they start the experiment.

**Experiment Questionnaire**

1 - How did you find the task involved in the experiment in the first days?

a) Very Hard  b) Hard  c) Neutral  c) Easy  d) Very Easy

2 - How did you find the task involved in the experiment in the last days?

a) Very Hard  b) Hard  c) Neutral  c) Easy  d) Very Easy

3 – How do you feel about your task performance?

a) I did not feel improvement  a) Slowly I got better  b) Suddenly I got better  d) I don't know

4 – Were you comfortable while doing the task in the first days?

a) Very uncomfortable  b) Uncomfortable  c) Neutral  c) Comfortable  d) Very comfortable

5 – Were you comfortable while doing the task in at the last days?

a) Very uncomfortable  b) Uncomfortable  c) Neutral  c) Comfortable  d) Very comfortable

6 – Did you face any difficulty while doing the task? If yes please explain.

a) No  b) Yes, the difficulty was …………………………………………………………………………………….

…………………………………………………………………………………………………………………………………………….

7 – Did you get bored while doing the task? If yes when did it get boring? (Please write free text)

8 – Did you get tired while doing the task? If yes when did it get boring? (Please write free text)

9 – Do you think you have become an expert in this task? (Please write free text)

10 – Do you think the robot helped you or blocked you doing your task? (Please write free text)

**Figure 20:** The experiment questionnaire which was given to the participants after they completed the experimental sessions

| | Question1: How did you find the task involved in the experiment in the first days?<br>1) Very Hard 2) Hard 3) Neutral 4) Easy 5) Very Easy | Control Condition |
|---|---|---|
| Subject 1 | Hard | Shared Control |
| Subject 2 | Hard | |
| Subject 3 | Neutral | |
| Subject 4 | Hard | |
| Subject 5 | Neutral | |
| Subject 6 | Neutral | |
| Subject 7 | Hard | |
| subject 8 | Easy | |
| Subject 9 | Easy | |
| subject 10 | Hard | |
| Subject 11 | Easy | Human Control |
| subject 12 | Hard | |
| subject 13 | Neutral | |
| subject 14 | Hard | |
| subject 15 | Hard | |
| subject 16 | Hard | |
| subject 17 | Very hard | |
| subject 18 | Hard | |
| subject 19 | Neutral | |
| subject 20 | Hard | |

**Table 12:** Experiment questionnaire - Participants answers to Question 1

| | Question2: How did you find the task involved in the experiment in the last days?<br>1) Very Hard 2) Hard 3) Neutral 4) Easy 5) Very Easy | Control Condition |
|---|---|---|
| Subject 1 | Easy | Shared Control |
| Subject 2 | Easy | |
| Subject 3 | Very Easy | |
| Subject 4 | Neutral | |
| Subject 5 | Easy | |
| Subject 6 | Very Easy | |
| Subject 7 | Neutral | |
| subject 8 | Very Easy | |
| Subject 9 | Very Easy | |
| subject 10 | Easy | |
| Subject 11 | Easy | Human Control |
| subject 12 | Easy | |
| subject 13 | Very Easy | |
| subject 14 | Easy | |
| subject 15 | Easy | |
| subject 16 | Neutral | |
| subject 17 | Very Easy | |
| subject 18 | Neutral | |
| subject 19 | Easy | |
| subject 20 | Easy | |

**Table 13:** Experiment questionnaire - Participants answers to Question 2

| | Question3: How do you feel about your task performance?<br>1) I did not feel improvement 2) Slowly I got better<br>3) Suddenly I got better 4) I don't know | Control Condition |
|---|---|---|
| Subject 1 | Suddenly I got better | Shared Control |
| Subject 2 | Slowly I got better | |
| Subject 3 | Slowly I got better | |
| Subject 4 | Slowly I got better | |
| Subject 5 | Suddenly I got better | |
| Subject 6 | Slowly I got better | |
| Subject 7 | Slowly I got better | |
| subject 8 | Slowly I got better | |
| Subject 9 | Slowly I got better | |
| subject 10 | Slowly I got better | |
| Subject 11 | Slowly I got better | Human Control |
| subject 12 | I don't know | |
| subject 13 | Suddenly I got better | |
| subject 14 | Slowly I got better | |
| subject 15 | Slowly I got better | |
| subject 16 | Slowly I got better | |
| subject 17 | Slowly I got better | |
| subject 18 | Slowly I got better | |
| subject 19 | Slowly I got better | |
| subject 20 | Slowly I got better | |

**Table 14:** Experiment questionnaire - Participants answers to Question 3

| | Question4: Were you comfortable while doing the task in the first days?<br>1) Very uncomfortable 2)Uncomfortable 3)Neutral<br>4) Comfortable 5) Very comfortable | Control Condition |
|---|---|---|
| Subject 1 | Neutral | Shared Control |
| Subject 2 | Neutral | |
| Subject 3 | Neutral | |
| Subject 4 | Neutral | |
| Subject 5 | Comfortable | |
| Subject 6 | Neutral | |
| Subject 7 | Neutral | |
| subject 8 | Uncomfortable | |
| Subject 9 | Very Uncomfortable | |
| subject 10 | Comfortable | |
| Subject 11 | Comfortable | Human Control |
| subject 12 | Neutral | |
| subject 13 | Very Comfortable | |
| subject 14 | Comfortable | |
| subject 15 | Comfortable | |
| subject 16 | Uncomfortable | |
| subject 17 | Uncomfortable | |
| subject 18 | Uncomfortable | |
| subject 19 | Neutral | |
| subject 20 | Uncomfortable | |

**Table 15:** Experiment questionnaire - Participants answers to Question 4

| | Question5: Were you comfortable while doing the task in the last days?<br>1) Very uncomfortable 2)Uncomfortable 3)Neutral<br>4) Comfortable 5) Very comfortable | Control Condition |
|---|---|---|
| Subject 1 | Comfortable | Shared Control |
| Subject 2 | Comfortable | |
| Subject 3 | Very Comfortable | |
| Subject 4 | Comfortable | |
| Subject 5 | Very Comfortable | |
| Subject 6 | Comfortable | |
| Subject 7 | Comfortable | |
| subject 8 | Comfortable | |
| Subject 9 | Very Comfortable | |
| subject 10 | Comfortable | |
| Subject 11 | Comfortable | Human Control |
| subject 12 | Comfortable | |
| subject 13 | Very Comfortable | |
| subject 14 | Comfortable | |
| subject 15 | Comfortable | |
| subject 16 | Neutral | |
| subject 17 | Very Comfortable | |
| subject 18 | Comfortable | |
| subject 19 | Comfortable | |
| subject 20 | Neutral | |

**Table 16:** Experiment questionnaire - Participants answers to Question 5

| | Question6: Did you face any difficulty or problem while doing the task? If yes please explain. | Control Condition |
|---|---|---|
| Subject 1 | NO | Shared Control |
| Subject 2 | NO | |
| Subject 3 | Sometimes ball would not stop, although I was sure that that the position of the tray | |
| Subject 4 | NO | |
| Subject 5 | Mouse collection or maybe another one that sometimes it was not working | |
| Subject 6 | NO | |
| Subject 7 | NO | |
| subject 8 | In the first day because of my position to the robot and my height. I coult not see points clearly so I stand on the tip of my shoes which made me tired. | |
| Subject 9 | NO | |
| subject 10 | NO | |
| Subject 11 | The surface of the ball and the noise and sound of other people working lab but not such a big difference | Human Control |
| subject 12 | To move the ball when very close to goal because it would not respond to small inputs | |
| subject 13 | That point 4 was a bit harder to reach to maybe because of a small deflection | |
| subject 14 | NO | |
| subject 15 | Point 4 | |
| subject 16 | NO | |
| subject 17 | NO | |
| subject 18 | NO | |
| subject 19 | NO | |
| subject 20 | I had to stand on the chair too see the ball | |

**Table 17:** Experiment questionnaire - Participants answers to Question 6

| | Question7: Did you get bored while doing the task? If yes when did it get boring? (Please write free text) | Control Condition |
|---|---|---|
| Subject 1 | NO | Shared Control |
| Subject 2 | No I didn't | |
| Subject 3 | NO | |
| Subject 4 | NO | |
| Subject 5 | 3 rd day, I was bored a little because I cannot control it. Otherwise it was good | |
| Subject 6 | NO | |
| Subject 7 | A little bit | |
| subject 8 | NO | |
| Subject 9 | NO | |
| subject 10 | NO | |
| Subject 11 | No it is not boring. Actually I enjoyed it | Human Control |
| subject 12 | It did not felt boring | |
| subject 13 | No just sometimes when it was taking more than normal to reach a point I was angry than bored | |
| subject 14 | Yes.This started after the being ties in the 4th point | |
| subject 15 | Point 4 made me bore. After several attempt to get the ball on point 4 got a bit more bored | |
| subject 16 | When it was getting so long | |
| subject 17 | First day when it was so hard for me it was bored, but day by day its was funny | |
| subject 18 | No | |
| subject 19 | sometimes, when I was unable to stop the ball | |
| subject 20 | NO | |

**Table 18:** Experiment questionnaire - Participants answers to Question 7

| | Question8: Did you get tired while doing the task? If yes when did you get tired? (Please write free text) | Control Condition |
|---|---|---|
| Subject 1 | NO | Shared Control |
| Subject 2 | Not tired per se but frustrated because a single task would take much time | |
| Subject 3 | NO | |
| Subject 4 | NO | |
| Subject 5 | NO | |
| Subject 6 | NO | |
| Subject 7 | NO | |
| subject 8 | NO | |
| Subject 9 | NO | |
| subject 10 | NO | |
| Subject 11 | No, for me this task was like a game and I had fun | Human Control |
| subject 12 | After around 10 tries | |
| subject 13 | I didn't | |
| subject 14 | Yes, and I guess the reason was due to the uneven ball | |
| subject 15 | NO | |
| subject 16 | When it was getting so long | |
| subject 17 | NO | |
| subject 18 | NO | |
| subject 19 | sometimes, when I was unable to stop the ball | |
| subject 20 | Sometimes. | |

**Table 19:** Experiment questionnaire - Participants answers to Question 8

|  | Question9: Do you think you have become an expert in this task? (Please write free text) | Control Condition |
|---|---|---|
| Subject 1 | Maybe | Shared Control |
| Subject 2 | Maybe I can say that with further practice I will become an expert with the help of the robot. The more I could learn it's behaviour and my own shortcoming, the better I could cover my weakness with robots behaviour. | |
| Subject 3 | Yes. I can do it much easier | |
| Subject 4 | No its still difficult for me | |
| Subject 5 | Yes. I like the control objects before the universities. I was clothes -designer. | |
| Subject 6 | Maybe | |
| Subject 7 | No but maybe with time I get better in this task | |
| subject 8 | Yes I think so. I did the experiment better than before | |
| Subject 9 | Kind of | |
| subject 10 | Not an expert but I got better. I mean it is iterative learning. Every new trial is better in terms of performance | |
| Subject 11 | I don't know. Maybe my results should be compared to other participants then I should have an opinion about that | Human Control |
| subject 12 | NO | |
| subject 13 | yes I have tested several tactitcts at he first day and focused on the one I was good at. | |
| subject 14 | Not expert but somehow I felt improvement | |
| subject 15 | I need some time | |
| subject 16 | NO | |
| subject 17 | Still I am not sure | |
| subject 18 | No | |
| subject 19 | not expert but improved | |
| subject 20 | I don't know | |

**Table 20:** Experiment questionnaire - Participants answers to Question 9

| | Question10: Do you think the robot helped you or blocked you doing your task? (Please write free text) | Control Condition |
|---|---|---|
| Subject 1 | It helped after second time | Shared Control |
| Subject 2 | It's absolutely helping. I just needed to learn it's behaviour then I could act in a way to help robot understand my goal and help me achieve it. | |
| Subject 3 | I think yes, although sometimes it would block me | |
| Subject 4 | Robot was helping! It was totally obvious | |
| Subject 5 | Robot blocked me many times. Especially when I move fast | |
| Subject 6 | Yes it helped | |
| Subject 7 | Yes it helps me | |
| subject 8 | In the 3rd day of the experiment I feel extra vibration while I was doing the task | |
| Subject 9 | It helped | |
| subject 10 | It did not helped me | |
| Subject 11 | No I don’t think so. The robot does not have any role I think | Human Control |
| subject 12 | Robot did not help | |
| subject 13 | The test day I felt some vibrations that are not due to my command, there I had the impression the the robot was actualy helping me but it did not bother me | |
| subject 14 | The robot, the interaction and the interface ( mouse control) was perfect The problem was the uneven ball | |
| subject 15 | I think robot played against me. It took control over the task | |
| subject 16 | I don't know | |
| subject 17 | First day it blocked me because it was look like and feel like too sensitive after it helped to me | |
| subject 18 | It did not help me! At all!!! | |
| subject 19 | I didn't have such feelings | |
| subject 20 | It didn't help | |

**Table 21:** Experiment questionnaire - Participants answers to Question 10

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