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# Cooperative human-robot control based on Fitts' law

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*Abstract*— **Many studies on human motor control have examined how humans move the arms. A well known phenomenon known as the Fitts' law describes the trade-off between the speed of motion and its accuracy. In robotics, many studies were performed, and different control methods were proposed, for robots working in well structured environments. Nevertheless, the cooperation between humans and robots remains a challenging task that is highly relevant for robots aiming to work together with humans in non-structured environments. In this paper we propose a novel method for on-line adaptation of robotic trajectories, where humans and robots are autonomous agents coupled through physical interaction, for example through manipulated object. Within the proposed framework, the robot adapts to the human motion through the sensory feedback by taking into account the Fitts' law where the user specific behavior is estimated using a recursive least square updates. The movement trajectories are represented by the Dynamic Movement Primitives, where the adaptation relies on the Iterative Learning Controller framework. The proposed approach was evaluated by a cooperative human robot arm-reaching task on a plane. We tested the accuracy and efficiency of the proposed method, showed its relevance and demonstrated that the proposed approach fully adapts to the human motor control and maintains the desired accuracy of the movement.**

## I. INTRODUCTION

Until recently, robots were mostly limited to work in industry and physically isolated from humans. However, with the recent rapid advances, the robots are slowly expanding into our every-day environments. Consequently the interaction and cooperation between humans and robots became an interesting yet a challenging topic of robotic research. One of the most challenging topics is the physical human-robot cooperation, where the robot works as a partner together with a human while complying with strict safety requirements.

The field of physical human-robot cooperation received considerable attention in the recent decade. Operating in unstructured environment was considered in [1], where the collision free paths and object manipulations were discussed but without directly taking into account the human physical interaction. The importance of physical interaction between the human and the robot was also highlighted in [2]. Human robot cooperation while being physically coupled through manipulated object was recently studied in [3]. Similarly, for gaining new behaviors, physical interaction in conjunction with different learning methods was described in [4], [5], [6]. An in-depth review of different approaches for physical human-robot cooperative interaction is in [7].

To establish an efficient shared control for cooperative tasks between the human and the robot, control systems should be designed with careful consideration of what the human feels [8], especially for applications involving wearable robots. One of the most common control concept that addresses this issue is based on the impedance control algorithms [9], [10]. This approach relies on producing force outputs such as damping and spring force in response to the movement of the arms. To detect and eliminate possible self-initiated movements, different sensory systems could also be used, i.e. force sensors or surface electromyographic sensors as in[11]. Even though such systems are inherently stable and allow certain degree of free movement, they are all based on the assumption that the desired robot movement is known. But until now, the desired robot movements were not based on dynamical and biomechanical properties of the human body. This is, however, a major disadvantage considering the fact that a robot should work with humans and assist the movement without inducing additional dynamic behavior. In terms of human-robot cooperation this means that the robot needs to be fully transparent for the user, i.e. the robot should help the user without slowing her/him down.

To design robot controllers for cooperative tasks that involve physical human-robot cooperation it is important to take into account also the neurophysiological aspects of human motion. In the past, the field of human motor control was mainly focused to analyse and model central nervous system during arm motor control during isolated arm movements [12], [13], [14], [15] and/or movements performed in the interaction with the environment [16]. They found out that despite the redundancy of the human arm, upper extremity movements are highly stereotyped. It was shown that these stereotypical movements can be successfully characterized with the bell-shaped velocity profiles [17], [18] and the speed-accuracy trade-off model also known as the Fitts' law [19], [20], [21]. Fitts' law is an empirical law developed to encode the speed-accuracy trade-off in arm-reaching tasks [19] where the time to complete a desired reaching movement can be expressed as a logarithmic function of the size of the target and the distance to the target.

In this paper we propose a novel control framework for human-robot cooperative tasks that links the impedance control approach with a computational model of the Fitt's law. To account for subject-specific anthropometric parameters we implemented a method to iteratively learn the parameters of the model. To fully characterize the motion we encoded the movement trajectories using Dynamic Movement Primitives and exploited their explicit time independence in conjunction with the model of the Fitt's law

To evaluate the proposed approach, we performed a series of experiments where the human subjects performed a task

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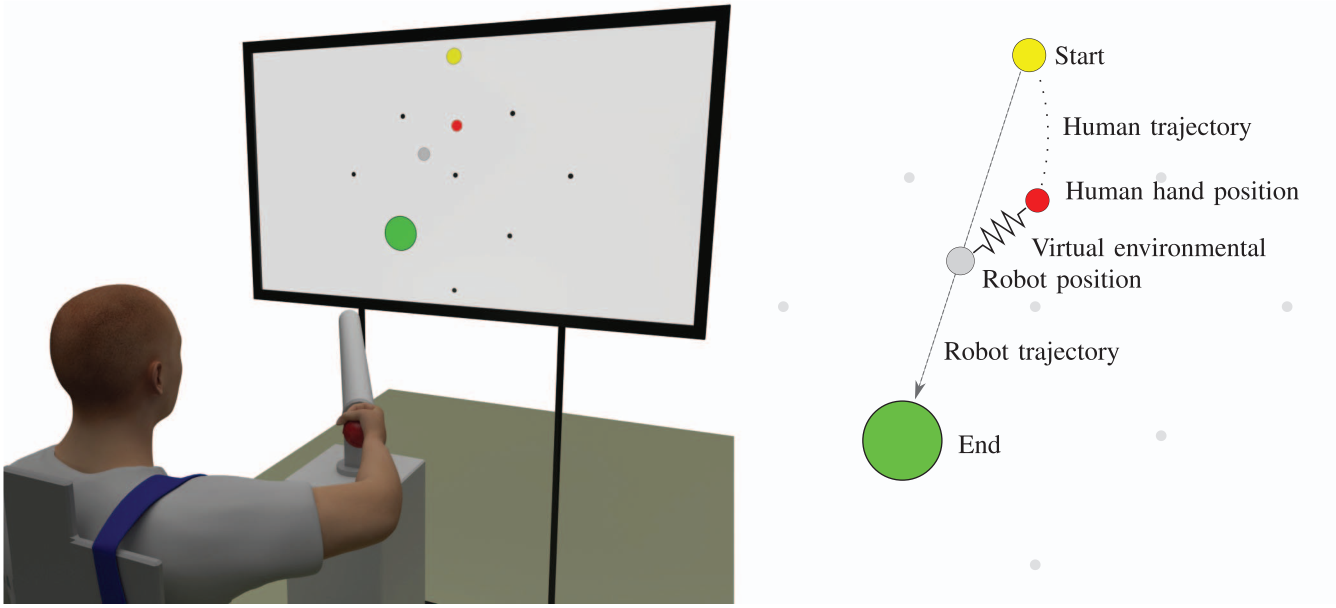


Fig. 1. Illustration of the experimental setup together with the detailed view of the screen.

together with a haptic robot. The human arm was physically coupled with the haptic device (Moog HapticMaster Mk. 2), allowing us to emulate the dynamics of the environment, i.e. the spring-damper system between the hand of the subject and the virtual position of the robot (see the illustration on Fig. 1). Our approach allowed us to emulate a human-robot cooperative task where the human and the robot are physically coupled through a compliant object. We analyzed the performance of eight healthy subjects performing the cooperative task of moving an object from a starting position towards several targets, i.e. task which simulates the cooperative object manipulation. The performance of reaching was assessed by measuring the actual and the estimated time of movement, the shape properties of the movement, and by measuring the difference between the human wrist and the end-effector of the robot.

This paper is organized as follows. In section II we describe the unified control approach for physical human robot cooperation. In Section III the proposed approach is validated on a task of cooperative manipulation while in Section IV we discuss on the possibilities and the impact of our work.

## II. CONTROL METHOD

Human arm movements have a typical bell-shaped profile during tasks like point-to-point arm reaching [17], [18], [19], [20], [21]. Moreover, a simple yet profound law known as Fitts' law explains the well known speed-accuracy trade-off when humans reach for objects of different sizes and at different distances. To integrate both properties of human arm movements into the robot control algorithm we propose a novel framework where a Fitts' law model is integrated into the Dynamic movement primitives.

### A. Fitts' law

The essential feature of the Fitts' law model is the speed-accuracy trade-off resulting in the time $T$ required to reach the target. To derive the method for human robot cooperation while reaching towards target we adopted the Fitts' model [19], [21], [20] described by

$$T = \zeta_1 + \zeta_2 \; ID = [1 \; ID]\boldsymbol{\zeta} = \boldsymbol{\Upsilon}'\boldsymbol{\zeta}, \tag{1}$$

where $T$ is the movement time, $\boldsymbol{\zeta}$ is the vector of user-specific parameters. Note that the parameters for the Fitts' law model are different for each individual. $ID$ denotes the index od difficulty, and for reaching tasks is defined as

$$ID = log_2\left(\frac{2D}{W}\right). \tag{2}$$

Here, $D$ is the distance towards the target, and $W$ is the width of the target.

To obtain proper parameters $\boldsymbol{\zeta}$, which are user specific, we proposed an algorithm where parameters $\boldsymbol{\zeta}$ are updated recursively after each trial, i.e. after each executed reaching movement. The recursive least squares updates for the Fitts' law are given by

$$\mathbf{P}_{n+1} = \frac{1}{\lambda}\left(\mathbf{P}_n - \frac{\mathbf{P}_n\boldsymbol{\Upsilon}\boldsymbol{\Upsilon}'\mathbf{P}_n}{\lambda + \boldsymbol{\Upsilon}'\mathbf{P}_n\boldsymbol{\Upsilon}}\right), \tag{3}$$

$$\boldsymbol{\zeta}_{n+1} = \boldsymbol{\zeta}_n + \mathbf{P}_{n+1}\boldsymbol{\Upsilon}\left(T_{n+1} - \boldsymbol{\zeta}_n'\boldsymbol{\Upsilon}\right)', \tag{4}$$

where $\lambda$ is the forgetting factor and $T_{n+1}$ is the actual execution time to needed to perform the movement. If not stated otherwise, we use $\boldsymbol{\zeta}_0 = [0 \; 1]'$, $\mathbf{P}_0 = 10 * \mathbf{I}_2$ and $\lambda = 0.995$.

By using the proposed updates for the Fitts' law model we can recursively tune the model to fit each individual user. Note that the Fitts' law model output is the time $T$, which defines the duration of motion for a given task, that is defined with the $ID$. For each subsequent task, given with new $ID$, we can then compute the movement time $T$. The computed movement time $T$ is then used to determine the duration of the Dynamic Movement Primitives.

### B. Dynamic Movement Primitives

The Dynamic Movement Primitives are used to encode the user specific movement trajectories, which are dependent on the particular task. For example, for the arm reaching task the arm movements usually follow bell-shaped trajectories [17], [18]. With a given movement time $T$, calculated based on Fitts' law, we can normalize the movement trajectory and hence make it time invariant. Note that for a reaching movements, the movement profile is similar for different target sizes and lengths, but scaled only in time. The time invariant trajectory can then be encoded into the DMP framework.

A short recap of the periodic DMPs [22], [23] with the extension for discrete movements is given next. Within this framework the trajectories can be given in either joint or task space. For each DOF, the movement trajectory is governed by the following differential equations

$$\begin{aligned} \dot{z} &= \Omega\left(\alpha_z\left(\beta_z\left(g-y\right)-z\right)+f(\phi)\right), \quad (5)\\ \dot{y} &= \Omega z. \quad (6) \end{aligned}$$

where the linear part ensures that the system $y$ converges to the desired goal $g$. The nonlinear part $f(\phi)$ is defined as a linear combination of radial basis function $\Psi_i(\phi)$. They are governed by

$$\begin{aligned} \boldsymbol{F}(\phi) &= \frac{\sum_{i=1}^{N} w_i \Psi_i(\phi)}{\sum_{i=1}^{N} \Psi_i(\phi)}, \quad (7)\\ \Psi_i(\phi) &= \exp(h(cos(\phi-c_i)-1)), \quad (8) \end{aligned}$$

where, $N$ defines the number of Gaussian like kernel functions, weighted with $\mathbf{w}$ that defines the actual shape of the movement trajectory. The variable $h$ defines the widths, and $c_i$ defines the centers of the kernels, respectively. The DMPs are not explicitly time dependent but only via the phase variable $\phi$ which is updated with

$$\dot{\phi} = \Omega = \begin{cases} \frac{1}{T}, & \text{if } \phi \leq 1 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

where $T$ defines the total duration of motion. Note that here $T$ is computed using the Fitt's law model (see Section II-A). To encode the DMPs, the weight vector $\mathbf{w}$ needs to be learned, for example, with incremental locally weighted regression, where the target data for fitting is

$$f_t = \frac{1}{\Omega^2}\ddot{p}_d - \alpha_z\left(\beta_z\left(g-p_d\right) - \frac{1}{\Omega}\dot{p_d}\right), \quad (10)$$

where $\ddot{p}_d$, $\dot{p}_d$ and $p_d$ are acceleration, velocity and position, respectively, of the target trajectory. Given the target $f_t$, $w_i$ is updated for each time-step $j$ with

$$\begin{aligned} w_{i,j+1} &= w_{i,j} + \Psi_i P_{i,j+1} e_j, \quad (11)\\ P_{i,j+1} &= \frac{1}{\lambda}\left(P_{i,j} - \frac{P_{i,j}^2}{\frac{\lambda}{\Psi_i} + P_{i,j}}\right), \quad (12)\\ e_j &= f_{t,j} - w_{i,j}. \quad (13) \end{aligned}$$

Here $P_i$ is the inverse covariance. The regression starts with $w_i = 0$ and $P_i = 1$. $\lambda$ is the forgetting factor set to $\lambda < 1$, typically at $\lambda = 0.998$.

## III. EVALUATION

### A. SUBJECTS

Eight healthy male volunteers (age = $28 \pm 5$(SD) years, height = $179 \pm 10$(SD) cm, weight = $74 \pm 8$(SD) kg) participated in the study. All subjects were right-handed and had no known neuromuscular or sensory disorders (self-reported). Prior to their participation, subjects were informed of the course of study and gave their informed consent in accordance with the code for ethical conduct at JSI.

### B. EXPERIMENTAL PROTOCOL

Subjects sat in front of a screen and were holding the haptic robot as shown in Fig. 1. They were instructed to hold the handle of the haptic device without bending the wrist. To constrain the motion of the trunk, the subjects wore a strap around the shoulder. The subjects were also instructed to hold their elbow on the same height as the shoulder joint. Movements made with the right arm were thus constrained to two degrees of freedom, i.e. shoulder and elbow rotations resulting in a planar motions. To ensure that subjects complied with given requirements, the experiments were visually monitored by the experimenter.

The experimental session began with a start and target circle appearing on the screen as shown in Fig. 1. The start and target circles ware chosen randomly from a pool of nine reachable positions as shown with black dots on Fig. 1. The size of the target circle was also random, with possible sizes of 1, 2 and 4 cm in diameter. The center of the pool of possible start and target circles was positioned straight up form the shoulder at the distance of $3/5$ length of outstretched arm. The current Cartesian position of the human arm was shown with red dot, and the desired robot position was shown as a gray dot. Note that the actual robot position is the same as the position of the human arm, due the tight physical coupling. Subjects were instructed to move the red dot (hand) into the start circle and wait for it to turn green. Their task was to move the hand form the start circle to the target circle as fast as possible. No further instructions were given except to move naturally and comfortably. They also had no knowledge of our proposed control method, neither it was explained to them prior to the experiment. The experiment lasted for total of 150 randomly chosen pairs of start and target circles with random sizes.

The task for the robot was to match the human arm movement as close as possible in terms of movement accuracy, i.e. match the movement duration time and movement trajectories. Note that movement profiles were adapted and encoded with DMPs and duration times were estimated with the proposed Fitts' law model adaptation. The virtual environment, i.e. interactive force between human and the robot (commanded robot position), was modeled and simulated as an interconnected spring-damper system (see right plot on Fig. 1) given as

$$\boldsymbol{f} = \mathbf{K}\boldsymbol{e} - \mathbf{D}\dot{\boldsymbol{e}}, \tag{14}$$

where $\boldsymbol{f}$ is the force exerted on the subject, $\boldsymbol{e}$ and $\dot{\boldsymbol{e}}$ are the position and velocity differences between the human arm and the desired robot position encoded by DMPs, respectively. $\mathbf{K}$ and $\mathbf{D}$ are spring and damping gains, set to 100 $\frac{N}{m}$ and 20 $\frac{Ns}{m}$, respectively. Ideally, when both models, i.e. Fitts' law model and movement profiles, converges the human arm position and robot end-effector position should be equal throughout the experiment.

### C. RESULTS

In Fig. 2 we show the adaptation of DMP weights $w_i$ for one representative subject during a full session. We can see fast adaptation of the weights $w_i$, even at the early beginning of the session, i.e. in the first trial. Note that the weights for DMPs are updated recursively in each time step, which allows certain degree of adaptation also in the first trial. We can see in Fig. 2 that the weights $w_i$ are close to the final learned values already in the first trial. This confirms our assumption that the movements, even with different distances to targets, target sizes and movement directions, can be well characterized by normalized movement profiles, and hence encoded as time invariant DMPs. Note that the final values of weights $w_{i,M}$ (blue colored dots on Fig. 2) deviates only slightly from intermediate values (gray colored dots on Fig. 2).

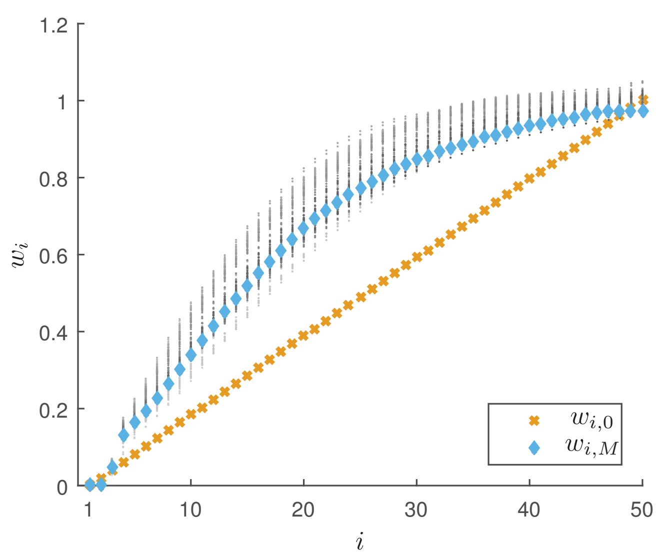


Fig. 2. Adaptation of DMP weights $w_i$ for one subject during one session. The initial weights $w_{i,0}$ are in orange and the final weights $w_{i,M}$ (after learning) are in blue. The intermediate steps are indicated with shades of gray, i.e. starting from bright gray at the beginning and going towards dark gray at the end of sesssion.

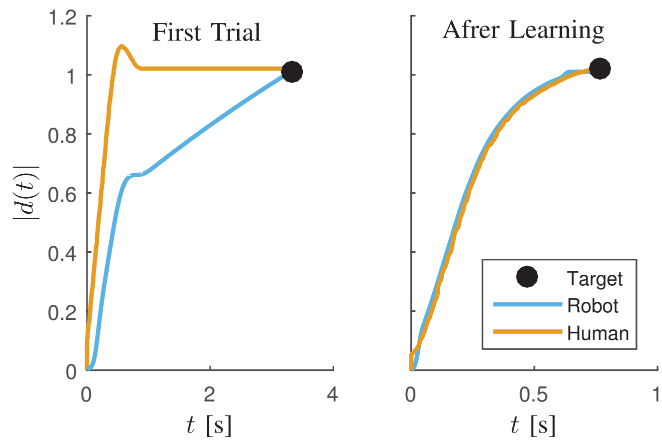


Fig. 3. Comparison of human and robot trajectories for the initial trial (left plot) and trial after the finished adaptation of the movement profiles and Fitts' law parameters (right plot).

The successful trajectory adaptation of the robot's motion profiles for the cooperative human-robot experiment is also shown in Fig. 3 where we show the initial human trajectory and the initial robot trajectory on the left hand side together with the final movement trajectories after the learning was completed. On the left plot of Fig. 3 we can see that the proposed control system, immediately starts adapting due to the nature of the recursive regression which we integrated at the DMP framework. However, since the initial estimated movement time is rather long with respect to the normal (actual) human movement time for reaching tasks, the error between the human arm trajectory and the robot trajectory is evident. Note that the expected movement time is calculated using the Fitts's law model where initial parameters were set to $\boldsymbol{\zeta}_0 = [0\ 1]'$. After learning, i.e. adaptation of both the movement profiles in DMPs and Fitts' law model parameters, we can see that the human movement trajectory is similar to the robot movement trajectory, i.e. there is no significant difference between the trajectories. This further supports our assumption that human movements in cooperation with the robot can be well charactered using the time invariant movement profile and modulated using the proposed Fitts' law iterative adaptation.

The analysis of convergence is shown in Fig. 4 where we show the mean and the standard deviation of the sum of the square errors between the robot trajectory and the human trajectory for the first 100 trials for all subjects. The error (one subject, one trial) was calculated by

$$\Delta(t) = \int_0^T (e(t)^2), \tag{15}$$

where $e(t)$ is the difference between the human arm position and desired robot position. As shown on the top plot of Fig. 4, the convergence of the proposed system is relatively fast. Note that the error stabilizes after 20 trials. Similarly we can see the evolution of the parameters for the Fitt's law model, i.e. parameters $\zeta_1$ and $\zeta_2$ on the middle and the bottom plots of Fig. 4. Here, we show the parameter

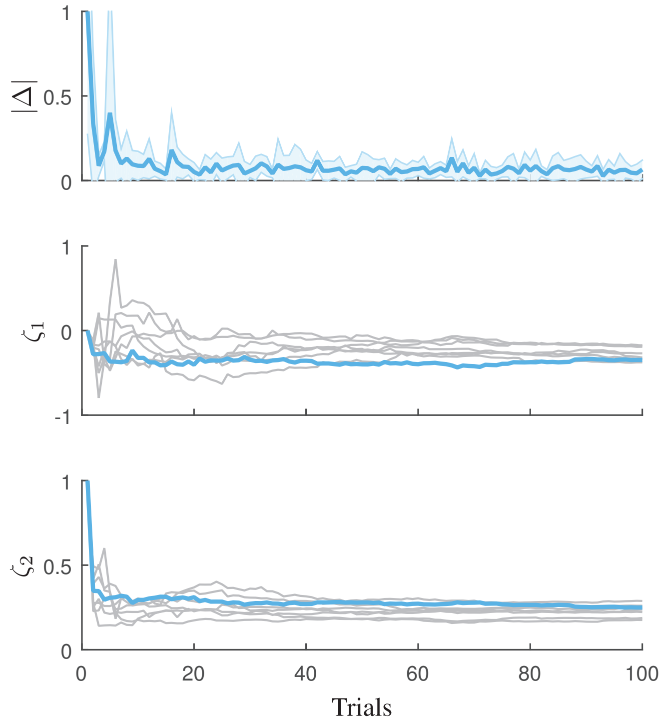


Fig. 4. The mean and the standard deviation of the sum of the square error between the human trajectory and the robot desired trajectory for the first 100 trials of all subjects. The middle and the bottom plots show the updates of the Fitts' law parameters for each subject (gray lines), for $\zeta_1$ and $\zeta_2$ respectively. For clarity, a representative subject is shown in blue.

evolution for all subjects together. An important observation was that the proposed system was able to converge for all subjects.

As expected, the Fitts' law model is subject specific, and therefore the parameters are different for each subject. With this in mind the data for the Fitts' law model was analyzed separately for each subject. The detailed Fitts' law model for each subject is shown in Fig. 5, where we show the relationship between the task difficulty and the required movement time (see Eq. (1) and (2)). In Fig. 5 we compare the actual movement times with the Fitts' law model times after learning. The results show that recursive regression in conjunction with the Fitts' law model was able to effectively converge and estimate the accurate movement times for a given task difficulty. This, together with the time invariant movement profiles encoded in DMPs, enables successful execution of physical human-robot cooperative tasks. Note that in the proposed approach the robot learns not only the movement profiles, but also the movement times required for successful task execution. The models for characterizing human arm movements have also a strong background in human motor control studies [17], [18], [19], [20], [21].

## IV. DISCUSSION

The aim of the work presented in this paper is to develop and evaluate a novel control approach for robots working with humans, where the control not only adapts to the human motion, but also takes into account human motor control properties. Instead of using methods that simply adapt to the human motion, we propose a method that takes into account specific models form human motor control studies. Specifically, for robot agents cooperating with humans to perform manipulation tasks, we take into account the well known Fitts' law which computationally explains the well known speed-accuracy trade-off [19], [20], [21]. Together with the trajectory learning methods that we integrated in formation of DMPs, this allows us to effectively model and perform cooperative tasks where the human and the robot are physically coupled. To evaluate the proposed approach we analyzed the performance of eight healthy subjects while performing a manipulation task in collaboration with the robot. Performance of the motion was assessed by measuring the differences in the movement profiles and the movement times between the human and the robot.

We found that the proposed control method successfully adapts the robot motion to the human subject and is able to effectively perform tasks where the human and the robot are cooperating in physical interaction. By analyzing the obtained data we show that with the proposed control method, the robot movements become almost identical to those of the human arm already after a few learning iterations. In the particular experiment it was shown that the desired robot movement became almost identical in less than 20 trials/iterations.

In terms of task difficulty $ID$, we have shown that the results are in compliance with the Fitts law findings reported in [19], [20], [21], i.e. larger targets are easier to hit, therefore the movements are faster and vice versa, smaller targets are more difficult to hit and therefore movements are slower and takes longer time to perform. We also show that our proposed method can successful estimate movement times, i.e. estimated times were similar to the measured ones. This implies that, together with the movement profiles, we can successfully characterize the arm reaching movements for a given human-robot cooperative task.

The study presented in this paper provides a clear indication that the proposed control method can be efficiently used for robots performing physical human-robot cooperative tasks. However, there are some limitations of this study. The evaluation was done only using one experimental setup where the humans were physically coupled with the robot (haptic device) and the environment was emulated. Also, the reaching task could be defined to be more challenging in terms of the dynamical requirements. Therefore, for our future work, we are planing to do the experiments where the human and the robot will have to move an object that will physically couple the human with the robot. As an example, one possible choice of the future experiment is the bi-manual human robot cooperation while closing the lid of the box [3].

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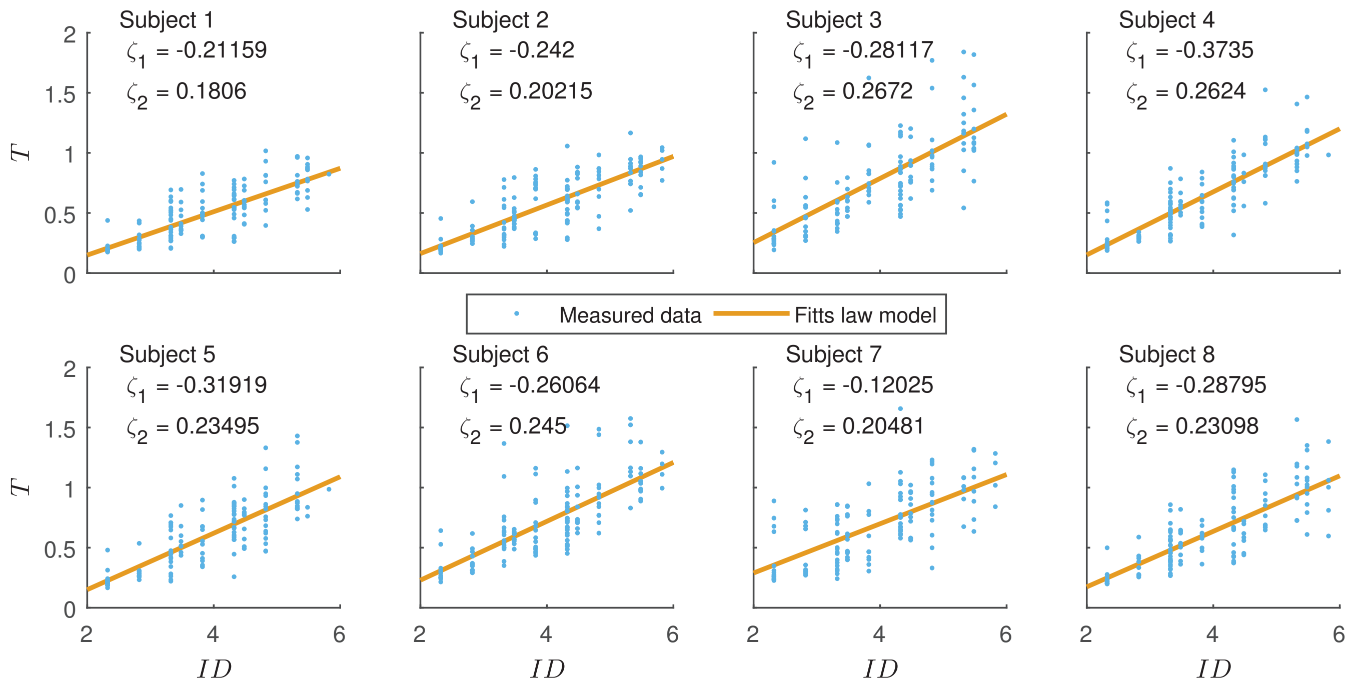


Fig. 5. Fitts' law models for all participated subjects.

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