# Fitts' law in the presence of interface inertia

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***Abstract*— Collaborative robots are advancing the healthcare frontier, in applications such as rehabilitation and physical therapy. Effective physical collaboration in human-robot systems require an understanding of partner intent and capability. Various modalities exist to convey such information between human agents, however, natural interactions between humans and robots are difficult to characterise and achieve. To enhance inter-agent communication, predictive models for human movement have been devised. One such model is Fitts' law. Many works using Fitts' law rely on massless interfaces. However, this coupling between human and robot, and the inertial effects experienced, may affect the predictive ability of Fitts' law.**

**Experiments were conducted on human-robot dyads during a target-directed force exertion task. From the interactions, the results indicate that there is no observable effect regarding Fitts' law's predictive ability.**

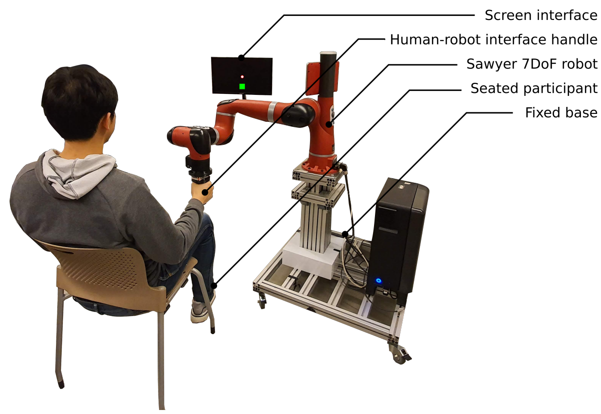



Fig. 1: The setup for the experiments.

## I. Introduction

In real-world applications, there are tasks that cannot be easily achieved by a single agent, whether robot or human. A dyad is a system comprising of two agents. It provides opportunities to expand the capability of a system by mitigating deficiencies and exploiting the strengths of its respective agents, e.g., combining human cognition with a robot's physical capability. However, effective dyadic interactions require an understanding of the partner's intent and their capability. Achieving such effective interaction implies that both agents are able to perceive, and most importantly, contribute in a meaningful way to achieve the shared goal.

In human-human dyads, conveying information is achieved through explicit verbal communication and implicit non-verbal interactions, including body language and touch. However, inter-agent understanding in human-robot dyads, require a protocol for robots to discern human interaction.

Historical experiments have shown that humans produce similar movements during target-directed reaching tasks [1]. A large number of models and approaches have been proposed to investigate the underlying reasons for the observed features during these movements. An analysis of spatio-temporal characteristics of target-directed reaching movements by [2] described how participants "generate roughly straight hand trajectories with single-peaked, bell-shaped speed profiles". This supported initial observations by [3] suggesting that multi-joint arm movements are planned in Cartesian space. However, observations of complex arm movements by [4] disputed the previous hypothesis by highlighting discrepancies in human velocity profiles, arguing that the bell-shaped velocity profile is not necessarily adhered to during motion.

Alternative theories on human motor command generation include simulations and observations by [1], which assert that human motion is planned using a staggered joint interpolation method. Further works by [5] demonstrated that a minimum torque change model can generate trajectories similar to those observed during target-directed reaching movements, unconstrained motion in a plane, and constrained motion under the influence of an external force.

One information-theoretic model for predicting human movement is Fitts' law [6]. Due to its simplicity, many works have utilised the model to guide their applications. Recent works using Fitts' law include [7] utilising the model to constrain electromyography classifications, [8] defining task difficulty through a fusion of physiological and kinematic metrics, and [9] predicting human intention during the generation of robot trajectories in collaborative workspaces.

One aspect of applying Fitts' law to physical systems, which is often neglected, is the device interface for humans. With most experiments relying on massless interactions, the effect of the human-device interface is rarely explored. A comparison of different interaction methods was conducted by [10], gauging the fit of Fitts' law when the interaction medium varies. While the study found similar trends between a mouse pointer and physical interactions with a target, the index of performance for gestural interactions were consistently below the other mediums due to participant unfamiliarity with the technology.

Given that the interaction medium affects the participant's performance, there is an ongoing need to explore the effects of various interaction mediums when designing experiments to validate Fitts' law. Specifically, in circumstances where inertial effects are experienced during the interaction. This work aims to identify whether the aforementioned effects experienced by participants, coupled to the end-effector of a collaborative robot, affect the predictive ability of Fitts' law during target directed movements. Furthermore, the effect of the inertia on the the highly stereotyped characteristics produced by these movements will be explored, in particular the human end-point trajectories and velocity profiles observed.

## II. Methodology

### A. Fitts' law

Fitts' law is a predictive model characterising target-directed human movement [6]. The model is defined as:

$$MT = a + b \cdot \log_2\left(\frac{2D}{W}\right), \tag{1}$$

where $MT$ is the movement time taken to reach a given target, $D$ is the distance from the target, and $W$ is the width size of the target. $a$ and $b$ are coefficients that are obtained heuristically through linear regression for each person. Fitts' law suggests that there is a relationship in human movement that depends on $D$ and $W$.

$$I_d = \log_2\left(\frac{2D}{W}\right), \tag{2}$$

The rate of information exchange in the motor system can then be calculated based on Shannon's information theory [11]. This produces the Index of Difficulty ($I_d$), measured in bits, indicating the amount of information associated with a task. Equation 3 is the Index of Performance ($I_p$), which is inversely proportional to the observed $MT$.

$$I_p = \frac{I_d}{MT}. \tag{3}$$

## III. Experiments

To observe the effects of the physical interaction medium on participant performance, an experiment was designed for human upper limb target-directed movements whilst coupled to a robotic manipulator. This coupled arrangement can be seen in robotic devices for rehabilitation [12] [13] and Assistance-As-Needed systems for industrial applications [14].

### A. Experiment Setup

In the experiment, shown in Figure 1, participants interacted with a 7 Degree-of-Freedom (DoF) robotic manipulator (HAHN Rethink Robotics, Rheinböllen, Germany). A 6-axis force-torque sensor (ATI Industrial Automation, Apex, NC) was affixed between a bespoke handle and the end-effector. The robot arm was programmed to enter a Cartesian impedance control mode native to Rethink Robotics' Intera SDK. This constrained movements to the X-Y plane parallel to the robot base at a height which was comfortable for seated participants.

Three different target widths (18.75mm, 37.5mm, and 56.25mm) and distances (120mm, 180mm, and 240mm) from the starting location of the end-effector were chosen for this experiment. The targets used for the experiments were arranged around the starting position of the participants hand. Additionally, impossible-to-reach locations were considered, thus removing targets that are occupied by the participants' body as shown in Figure 2. The participants did not have any prior knowledge of the possible target locations, and these locations were never visually displayed to participants until the experiment trials.

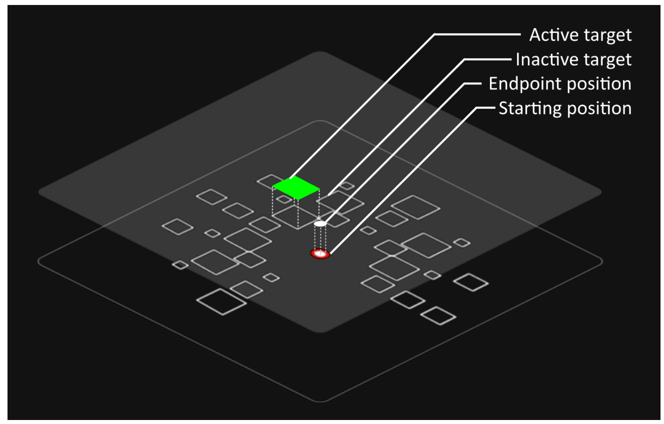



Fig. 2: The array of targets that participants were required to reach using the handle affixed to the end-effector. The two planes, grey and black, represent what the participants are shown during the experiments, and the array of targets that is never revealed. The current position of the end-effector is indicated by a filled white circle, while the center of the visual display is represented by the outline of the red circle.

### B. Human Participation Study

Ten healthy adults (9 males and 1 female) provided informed consent to participate in a target-reaching experiment approved by an ethics committee (UTS, Australia, approval number ETH18-3029). All participants were right-handed, and have no known neuromuscular or sensory disorders.

Participants were seated and instructed to keep their back against the chair so the affixed handle in its starting location is 0.55m away from their torso. Visual feedback for the experiment was communicated via a monitor screen in front of the participant, which displayed visual cues during the experiment.

Participants were instructed to move an on-screen marker, indicating the position of their hand, to the centre of a target as accurately and as quickly as possible. The participants were also instructed to move the handle towards the target while maintaining trunk posture to minimise torso movement. Specifically, they were asked move to the target in a single motion, and to refrain from performing postural corrective movements to improve their endpoint accuracy.

Prior to the experiment, a trial run was conducted so participants could familiarise themselves with the setup and experimental procedure. This is to help remove bias due to unfamiliarity with the experiment conditions. Each participant was asked to perform 28 trials in the experiment according to a predetermined sequence, which was only displayed one-step-ahead and never displayed to the participant in its entirety.

## IV. Results

Each target directed movement performed by the subjects were analysed to obtain the cofficients of Fitts' law. Table I shows the participants' Fitts' law coefficients (FLC) (Equation 1), calculated using linear least squares.

| FLC | Participant # | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| $a$ | 0.75 | 0.96 | 1.41 | 0.26 | 0.92 | 0.92 | 1.09 | 1.09 | 0.79 | 0.75 |
| $b$ | 0.17 | 0.02 | 0.19 | 0.55 | 0.15 | 0.18 | 0.07 | 0.07 | 0.09 | 0.06 |

TABLE I: The participants' coefficients from Fitts' law.

Although the Fitts' law model is personalised, an aggregation of the measured mean movement time and the associated $I_d$ for all participants are shown in Figure 3. The 95% confidence interval for each participants' movement time, and the predicted movement times illustrates the relationship between task difficulty and movement time with a $R^2$ value of 0.853. Furthermore, Table II shows the p-values associated with Figure 3, demonstrating that the presence of inertia during interactions yields an insignificant effect in this setup.

The targets for the trials were placed at one of three distances away from the starting position, as indicated by the 3 colors present in Figure 4(a). The shaded regions indicate the variation of velocity profiles between participants, supporting the notion of personalised parameters for Fitts' law. An aggregated endpoint velocity performed by participants was used to demonstrate the similarities that exist during the initial stage of the trajectories, as well as highlight the increase in peak velocity when the targets were located further away from the starting point.

The average velocity profile for the samples shown in Figure 4(b) demonstrates the single peak, bell-curved velocity profile nature of target directed movements. The two figures shown within the figure possess the same $I_d$, where target 1 is the first trial that uses that specified $I_d$, and target 25 is the last trial to use the $I_d$. The trial for target 1 is shown in the top figure of Figure 4(b) is slower to peak and converge to within the 0.1m/s threshold than the trial for target 25 shown in the graph below. This indicates that a learning component is exhibited by participants, however this effect is minimal.

To analyse the trajectories performed during the reaching motion, a subset of the targets were chosen. The targets selected were those located directly in front of, and behind the designated starting position of the trial. Although the most direct path to the target was a straight line trajectory, all participants exhibited curved paths toward the target. Furthermore, the curved paths were not bound to either side of the x axis as shown in Figure 4(c). The curved Cartesian trajectories are potentially an effect of the mechanical configuration of the manipulator predisposing its motion to either side of the plane.

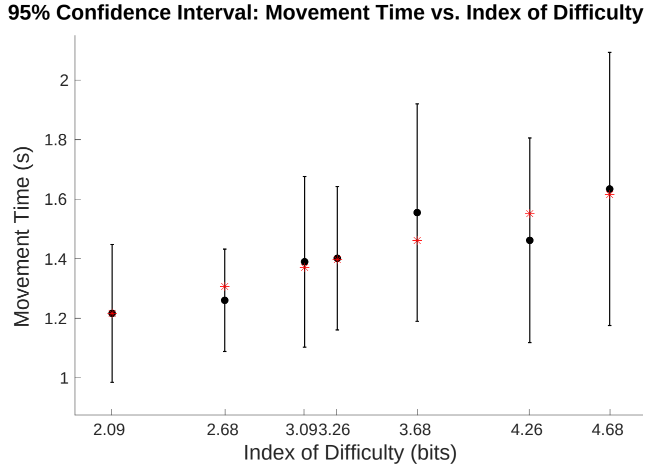



Fig. 3: The 95% confidence interval produced from the aggregation of mean movement times from each participant. The circle markers, error bars, and red asterisks indicate the sample mean movement time, bounds for the 95% confidence interval, and movement times, respectively, as predicted by Fitts' law.

## V. Discussion

This study aims to explore Fitts' law, specifically the model's ability to predict human movement behaviour during interactions that impose the effect of inertia.

The results from Figure 3 demonstrate that all predicted movement times lie within the 95% confidence interval, and the corresponding $p$-values shown in Table II indicate that there is not enough evidence to conclude whether target directed movements with an interface possessing a higher inertia compared to conventional interfaces used for Fitts' law studies (such as a stylus or a mouse).

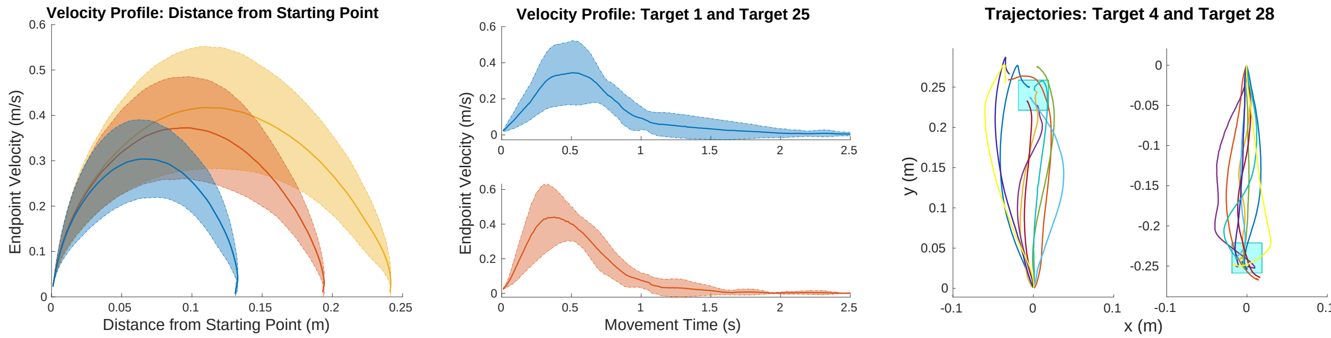
However, participants still exhibit movement characteristics associated with target directed movements, in particular the bell curved velocity profile shown in Figure 4(a)(b).

| $p$-values | | | | | | | |
|---|---|---|---|---|---|---|---|
| $I_d$ | 2.09 | 2.68 | 3.09 | 3.26 | 3.68 | 4.26 | 4.68 |
| p-value | 0.50 | 0.72 | 0.44 | 0.48 | 0.29 | 0.72 | 0.46 |

TABLE II: The $p$-values calculated from the aggregation of mean movement times from each participant and the predicted movement time given by Fitts' law.

One aspect to consider during the analysis of results obtained from the experiments is the visual feedback type provided to the participant. While the original experiment by Fitts [6] relied on physical target touching using a stylus, the experiments conducted utilise remote visual feedback. Without a physical target, participants relied on hand-eye coordination to estimate the location of the end-effector and target in Cartesian space.

The effects of the interaction medium can be characterised by the noisy velocity profile. It is hypothesised that the features from the interaction can be attributed to the robotic manipulator possessing Series Elastic Actuators. The elasticity from the springs within each joint can create potential parasitic dynamics when participants interact with the device. This contrasts to traditional Fitts' law tests which have




(a) (b) (c)

Fig. 4: (a) The average velocity profile performed by all participants against the distance of the end-effector from the starting point. The shaded regions indicate the standard deviation for the 3 target distances that surrounded the starting point. (b) The average velocity profile of all participants between an earlier trial vs. a later trial. The bounds of the standard deviation are indicated by the thinner line width, where the shaded region encapsulates the standard deviation. (c) Variations in participant trajectories as they reach two different targets. Both targets are a pure translation along the y-axis, in front (left) of and behind (right) the starting position of [0,0]. The cyan square represents the size of the target for each respective trial.

extensively explored human computer interactions which rely on interaction mediums without significant inertia and internal dynamics.

Additionally, the configuration of the manipulator produces varying inertia at the endpoint, thus affecting its susceptibility to move to either side of the x-axis. However, it can be seen that participants correct this motion in an attempt to finish the motion within the specified target, this correction adds another aspect that participants must consider during their movements.

It is worthwhile to disclose that the original design of experiments for Fitts' law subjected participants to "rapid and uniform responses that have been highly overlearned" [6]. This provided an experimental situation which was posited to be only limited by the capacity of information transfer in the motor system.

## VI. Conclusion

This paper explores the observed measurements and trends during target-directed movements with respect to Fitts' law. Although the presence of inertia during the interactions had no observable effect on Fitts' law's predictive power, and the well-observed bell-curved velocity profiles were maintained by all participants. Future work will seek to explore the dynamics of interactions within a coupled system, and incorporate simple metrics to enhance interactions between human-robot dyads, enabling improved protocols for therapy and rehabilitation incorporating physically assistive robots.

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