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Learning to Master Robotic Arm Movements with Bimanual Joystick Control: Indicators for Evaluating the Difficulty of Movement Tasks

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ABSTRACT

Manual control of robotic arms is challenging, and productive operators require extensive prior training. Effective training should systematically vary the difficulty level of the robot arm motions. This study investigates the extent to which Fitts' law could define movement difficulty for bimanual controlled movements of robotic arms. Inspired by forestry work-methods, we designed Fitts' tapping task to assess the movement time and throughput of ten unskilled participants over nine training sessions. We found that robotic arm movements observe Fitts' law for reaching in depth but deviate for lateral and concentric movements. In other words, training can utilize Fitts' law to vary the difficulty of forward robot arm movements. Further studies on the difficulty of lateral and concentric movements are necessary to refine work methods and improve training.

Keywords: Robotic arm movements, Machine operator behaviour, Bimanual control

INTRODUCTION

To control articulated robotic arms, such as forest harvesters, operators must learn how to simultaneously transform multiple independent degrees-of-freedom. Extensive simulator training and field training is currently necessary before operators are sufficiently skilled to operate safely and independently. Such training is costly and could be more efficient.

To begin, not all movements are equally difficult not likely to be required. Although operators are often expected to exert nimble and flexible control of robotic arms to actuate a diverse repertoire of manoeuvres and cope with all exigencies. On the other hand, some movements are typically more frequent than others, especially when the operational context is taken into consideration (Ranta, 2009). In forestry, the frequency of the robot arm (crane) movements result from well-specified work requirements. For instance, in clear felling, trees are required to be felled in the direction of travel (i.e., machine trail) and produced logs should be placed alongside the machine trail. The most productive methods are 'Two-Sided Piling' and Forward Felling' in clear cuts (Ovaskainen et al., 2011). Further, a narrow fell swath in the direction of travel increases productivity (Nordberg, 1987). Superfluous movements and trajectories, though possible, render operations inefficient (Ovaskainen et al., 2004). Currently, machine operators in training are only exposed to a variety of situations that place demands on the complexity of crane movements (e.g., number of segments served simultaneously, Wickens et al., 2013). Instead, tasks should be presented that scale with the growing aptitude of the trainee. However, it is unclear how movement difficulty ought to be defined and operationalized.

In human aiming movements, movement difficulty can be systematically varied using Fitts' tasks. The current work is motivated to situate the difficulty of moving robotic arms within a such a framework or one that is comparable. The movement difficulty of Fitts tasks are operationalized in terms of the information capacity of the human motor system (Fitts, 1954). Typically, subjects perform repetitive aiming movements to tap alternatingly between two targets. The information capacity required to perform this repetitive movement can be defined in terms of the size of the targets and the distance between them (Soukoreff and MacKenzie, 2004). The task is frequently amended for specific applications i.e., to evaluate performance of varying (tele-operated) robotic arm movements (Draper et al., 1990; Jung et al., 2013; Suzuki and Harashima, 2008). However, Fitts' task was originally intended to study human aiming movements and not the movement of robot arms.

In summary, the extent that Fitts' law can be applied to human controlled robotic arm motions in the forest context is unclear. Operator must move their arms to operate bimanual controls that actuate robotic arm movement. However, the amplitude of these manual movements do not correspond directly to the actuated robot arm movement—robot arm movement is indirectly controlled by the angular velocities of the robot joints. Thus, operators must learn a nonlinear transformation to map their own motor actions onto the robot arm. In this paper, we use Fitts' law as a theoretical framework to manipulate the difficulty of crane motions. If Fitts' law applies, manipulations of target distance and target size according to the relationships derived by Fitts should lawfully govern performance indicators such as movement time and information throughput (Fitts, 1954). Furthermore, we are interested in the extent that learning the robot arm movements affects Fitts' performance indicators.

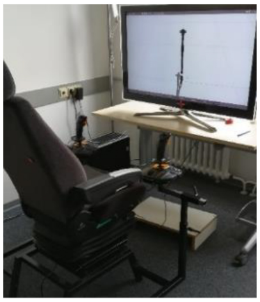
METHODS

Participants and Apparatus

Ten (6f, 4m) volunteers with an average age of $M_{age} = 28$ years ($SD_{age} = 9.29$) learned to operate a robotic arm simulator across nine successive sessions. All participants had no prior experience in the task and robotic arm control. The robotic arm simulator consisted of a Grammar seat (Chicago 1040673-C) with two mounted joysticks (Thrustmaster T.16000M FCS) and a Samsung 55” TV Screen (Samsung LE40C750R2Z). The simulation software comprised C++, ROS, and GAZEBO.

Robotic Arm Simulation and Stimuli

The simulation provided a manipulator (open manipulator) with four articulated joints and an end effector (gripper) (ROBOTIS Inc., Korea). The manipulator had 4 degrees of freedom and was simulated in GAZEBO. Participants were presented with a tilted view, centred on the manipulator on a gridded ground plane (Fig. 1).



(b) Purple targets (start right)

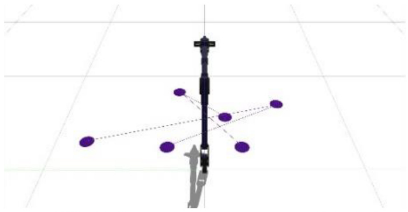
(a) Simulator setup

(c) Blue targets (start left)

Figure 1: Displayed is the simulator setup (a), the Targets in purple (b) and blue (c) colour are shown from the perspective of the participants.

Movement targets were displayed as blue and purple circle pairs ($W = 0.5$cm) on the ground plane. Blue indicated that tapping should begin on the left side and purple, the right side. There was a visible circle on each side of the robotic arm. The distances between them and their locations were selected such that the movement patterns (e.g. movement direction) were comparable with contemporary working methods (i.e., two-sided and forward felling; c.f. Ovaskainen et al., 2011). These diagonal patterns (Fig. 2) varied in amplitude (D, spacing) and required participants to exploit all possible DOFs of the robotic arm.

(a) Movement patterns (left)



(b) Movement patterns (right)

Figure 2: Shown are the predefined movement trajectories (a, start left; b, start right).

Fitts' law assumes that motor performance can be described by the mathematical concept of "information". The amplitudes of aiming movements are considered analogous to the information of transmitted signals, and the spatial accuracy (variability) of movements is considered analogous to system noise. Since Fitts' law treats the human motor system as a communication channel, the bandwidth (or information throughput) of movement can be expressed in bits/s. Thus, the difficulty of a motor task can be quantified by the difficulty index (*ID* in bits), which is the logarithmic ratio of *target distance* (*D*) and *target width* (*W*), $ID = \log_2 (D/W + 1)$. Fitts' law predicts that movement time (MT) increases linearly with the difficulty index *ID*, $MT = a + b\ ID$. The effective difficulty index $ID_e = \log_2 (D/W_e + 1)$ achieved is used to calculate information throughput $TP = (ID_e/MT)$ in [bits/s]. Here, the effective distance W_e, defined by the variability of the executed aiming movements, is taken into account (e.g., MacKenzie, 1992). The current study kept *target width* constant (W = 0,5cm) and *target distances* between circles (*D*) where selective to derive a effective ID range (*ID* =2.49, 3.09, 3.35, 3.92). Balanced for starting position, this resulted in eight target combinations (for further details see Soukoreff & MacKenzie, 2004).

Procedure

Participants first provided signed consent to written instructions. Next, the participants sat in the simulator and received task instructions, followed by a short training of four movements between targets ($W = 1.5$cm). Next, the task began, and participants tapped each target ten times, returning nine recorded movements for each randomized target within one experimental Block. A session consisted of six Blocks. Altogether, participants completed nine sessions and generated 4320 movements in total. A Session lasted from 3.5h to 1.5h depending on the learner's skill level and progression in the experimental series. After the task, participants filled a questionnaire on demographics and co-founding variables (i.e., joysticks use).

Design

The study was conducted as 2 (left, right) x 4 (index of difficulty) x 6 (Block) x 9 (Session) repeated-measurement design.

RESULTS

The data was pre-processed and analyzed in MATLAB (v.2021a) and R (v.4.1.1).

Performance and Learning

Task performance was operationalized as *MT* and *throughput*. According to Fitts' law, both are expected to increase with the *index of difficulty* of the aiming movements. An repeated-measures Analysis of Variance (ANOVA), with main factors of *ID* (4 levels) and Sessions (9 levels), showed a significant effect of *ID*s on movement times ($F(1.15, 10.39) = 38.10$, $p < .001$, $\omega^2_{\mathrm{p}} = 0.57$). Post-hoc pairwise Tukey adjusted comparisons revealed that

*MT*s increased with difficulty from *ID*s 2.49 to 3.35 bits and abruptly decreased for $ID = 3.92$ bits—*MTs* did not significantly differ between $ID = 3.92$ bits ($M = 8.51$s, $SD = 2.51$s) and $ID = 2.49$ bits ($M = 8.21$s, $SD = 2.89$s, $p = .212$; see Fig. 3).

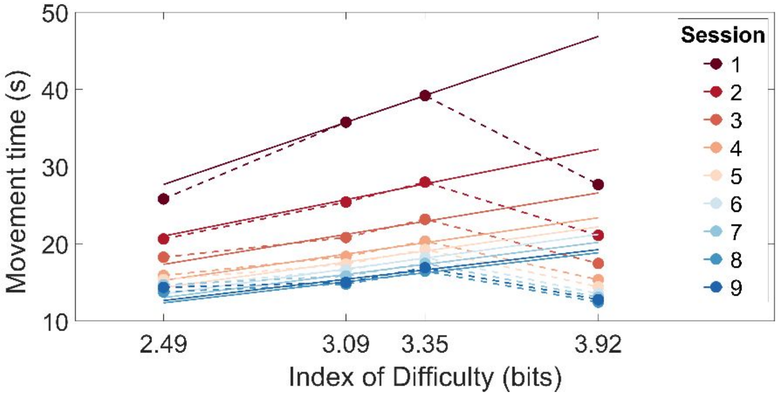


Figure 3: Movement time in seconds as a function of Fitts Index of Difficulty and experimental sessions. Dots indicate observed data and straight lines indicate linear prediction of movement time according to Fitts Law. Session is represented by color.

Two separate one-way repeated measures ANOVA were conducted to analyze the throughput for the factors of *ID* and *sessions* and revealed that *throughput* increases with higher *IDs*, ($F(1.04,\ 9.37) = 58.39\ p < .001$, $\omega^2{}_p = 0.66$) and later *session* ($F(8,\ 72) = 84.70\ p < .001$, $\omega^2{}_p = 0.007$) (c.f. Fig. 4).

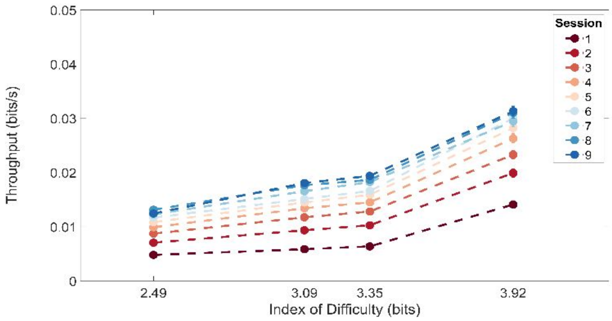


Figure 4: Throughput in bits/s per index of difficulty shown for each session, separately.

Learning Maximum

Throughput should increase with motor skill development but can be expected to be limited by the maximum achievable performance level. This could provide insights into remaining gains and the efficiency of the given training protocols. Thus, we expected throughput to increase with Sessions to the asymptotic maximum. We fitted an exponential function $V_{inf}+\alpha_s e^{-\gamma}{}_s{}^n$, where V_{inf} denotes performance that is the estimated maximum achievable TP, α_s is the start value, γ is the rate in increase of throughput and n the number of experimental sessions. The fitted exponential curves (Fig. 5) show that $ID = 3.92$ bits shows the highest maximum *throughput* with $TP_{3.92} = 0.032$ bits/s. This contrasts to the other *IDs* $TP_{2.49} = 0.02$ bits/s, $TP_{3.09} = 0.021$ bits/s, $TP_{3.35} = 0.014$ bits/s. Further, there was a significant interaction of *ID* and *session* ($F(24, 216) = 9.13$, $p = .001$, $\omega^2{}_p = 0.07$)). Learning plateaus with more training sessions and, hence, lower gains are achieved the closer performance gets to this asymptote. Mostly, skill development is achieved before expert level thus it is useful to have an approximation of when improvements are no longer significant. We performed planned Tukey adjusted contrasts for all consecutive sessions there were no significant differences after session four ($p_{1\text{-}2}; p_{2\text{-}3}; p_{3\text{-}4} < .001, p_{4\text{-}5} = 0.12, p_{5\text{-}6} = 0.84, p_{6\text{-}7} = 0.57, p_{8\text{-}9} = 1.00$)).

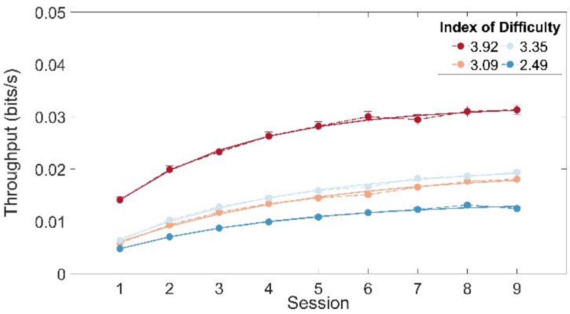


Figure 5: Information capacity (throughput in bits/s) plotted across experimental sessions by each index of difficulty. Solid lines show fitted function.

DISCUSSION

This study sought to clarify if Fitts' law could be applied to pre-determine the movement difficulty of robotic arm movements in forestry work methods. If true, it could inform the design of how tasks are scheduled for operator training. To this end, we evaluated how useful Fitts' index of difficulty is in defining the progression of acquired skill.

We found that movement time and throughput of the 4 DOF robotic arm followed the prediction of Fitts' law for three ($ID = 2.49$, 3.09, 3.35) out of four *ID*s independent of skill development over training. As expected, learning causes movement times to decrease and information throughput to increase with sessions. Both, movement time and information throughput showed saturation effects, that allowed to estimate the required maximum training effort and revealed that the $ID = 3.92$ bits appeared to stand out. Interestingly, movement time and throughput of the $ID = 3.92$

bits, do not agree with Fitts' predictions. Here, performance is surprisingly similar to $ID = 2.49$ bits. In other words, motor control for a task that was predicted to be difficult, was in fact, simpler to perform. Preliminary analyses suggest that our participants adopted a different motor control strategy for $ID = 3.92$ bits, which could have accounted for this non-linearity. The distance from left to right is mainly bridged by a slewing motion that can be realized by a single joystick axis input. In addition, the concentric movement allows for targets close to the orbit to reduce the invested joint range (overall or specific i.e., by not using the gripper). Such strategy facilitates control demand and would lead to an optimized speed compared to the lower presented IDs where movements are not close to the slewing orbit. Follow-up studies could verify this by assessing the effect of lateralization in *IDs and distance to the orbit of the concentric movement*.

Our study revealed that robotic arm movements' difficulty can be described for movements in front/in depth of the manipulator by Fitts' law. Selectively, training difficulty can thus be tailored in accordance with Fitts' *ID*. Concentric movements ease motions where the actual difficulty is yet to be systematically operationalized. In regard to forestry work methods, we can conclude for working close to the front midline that short tree handling distances are favorable over longer distances and larger tolerances over small tolerances in harvester head positioning. This is in line with work methods that recommend working close and in front of the machine. However, long movements that consist mostly of concentric, slewing motions keep up with short tree handling times and distances. Still lateral and concentric movements need further research on their actual demand and the application of Fitts should therefore be used with caution in movement difficulty description.

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REFERENCES

Draper, J.V., Handel, S., Hood, C.C., 1990. Fitts' Task by Teleoperator: Movement Time, Velocity, and Acceleration. PROCEEDINGS of the HUMAN FACTORS SOCIETY 34th ANNUAL MEETING- 5.

Fitts, P.M., 1954. The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement 8.

Jung, K., Chu, B., Park, S., Hong, D., 2013. An implementation of a teleoperation system for robotic beam assembly in construction. Int. J. Precis. Eng. Manuf. 14, 351–358. https://doi.org/10.1007/s12541-013-0049-3

MacKenzie, I.S., 1992. Fitts' Law as a Research and Design Tool in Human-Computer Interaction. Human–Computer Interaction 7, 91–139. https://doi.org/10.1207/s15327051hci0701_3

Nordberg, M. 1987. Feasibility of strip-road spacing less than 25m in thinnings - areport on trials in first thinnings. The Forest Operations Institute of Sweden, Kista, Report No. 3:33. ISSN 0346–6671.

Ovaskainen, H., Palander, T., Tikkanen, L., Hirvonen, H., Ronkainen, P., 2011. Productivity of Different Working Techniques in Thinning and Clear Cutting in a Harvester Simulator. BALTIC FORESTRY 17, 11.

Ovaskainen, H., Uusitalo, J., Väätäinen, K., 2004. Characteristics and Significance of a Harvester Operators' Working Technique in Thinnings. International Journal of Forest Engineering 15, 67–77. https://doi.org/10.1080/14942119.2004.10702498

Ranta, P., 2009. Added values of forestry machine simulator based training, in: Proceedings of the International Conference on Multimedia and ICT Education. Citeseer, Lisbon, p. 6.

Soukoreff, R.W., MacKenzie, I.S., 2004. Towards a standard for pointing device evaluation, perspectives on 27 years of Fitts' law research in HCI. International Journal of Human-Computer Studies 61, 751–789. https://doi.org/10.1016/j.ijhcs.2004.09.001

Suzuki, S., Harashima, F., 2008. Analysis of machine operation skills using hand discrete movement. Presented at the 2008 International Conference on Control, Automation and Systems, pp. 2824–2829. https://doi.org/10.1109/ICCAS.2008.4694240

Wickens, C.D., Hutchins, S., Carolan, T., Cumming, J., 2013. Effectiveness of Part-Task Training and Increasing-Difficulty Training Strategies: A Meta-Analysis Approach. Hum Factors 55, 461–470. https://doi.org/10.1177/0018720812451994