Subjective Difficulty and Indicators of Performance of Joystick-based Robot Arm Teleoperation with Auditory Feedback

Nikolaos Mavridis
Institute of Informatics and Telecommunications
NCSR Demokritos
Athens, Greece
nmavridis@iit.demokritos.gr

Georgios Pierris
Institute of Informatics and Telecommunications
NCSR Demokritos
Athens, Greece
gpierris@iit.demokritos.gr

Paolo Gallina
Dept. of Engineering and Architecture
University of Trieste
via Valerio, 10, 34127, Trieste, Italy
pgallina@units.it

Nikolaos Moustakas
School of Medicine
Aristotle University of Thessaloniki
Thessaloniki, Greece
nikolisdex@gmail.com

Alexandros Astaras
Dept. of Computer Science
American College of Thessaloniki
Thessaloniki, Greece
astaras@act.edu

***Abstract*—Joystick-based teleoperation is a dominant method for remotely controlling various types of robots, such as excavators, cranes, and space telerobotics. Our ultimate goal is to create effective methods for training and assessing human operators of joystick-controlled robots. Towards that goal, an extensive study consisting of a total of 38 experimental subjects on both simulated as well as a physical robot, using either no feedback or auditory feedback, has been performed. In this paper, we present the complete experimental setup and we report only on the 18 experimental subjects teleoperating the simulated robot. Multiple observables were recorded, including not only joystick and robot angles and timings, but also subjective measures of difficulty, personality and usability data, and automated analysis of facial expressions and blink rate of the subjects. Our initial results indicate that: First, that the subjective difficulty of teleoperation with auditory feedback has smaller variance as compared to teleoperation without feedback. Second, that the subjective difficulty of a task is linearly related with the logarithm of task completion time. Third, we introduce two important indicators of operator performance, namely the Average Velocity of Robot Joints (AVRJ), and the Correct-to-Wrong-Joystick Direction Ratio (CWJR), and we show how these relate to accumulated user experience and with task time. We conclude with a forward-looking discussion including future steps.**

I. Introduction

Teleoperation is a field with its beginnings in the second half of the twentieth century, which has proved to be invaluable in a number of application domains, where autonomy is either above the state-of-the-art, prohibitively expensive, or where ethical and legal aspects necessitate the existence of a human operator. Quite importantly, teleoperation usually covers cases where the physical existence of a human operator in the task space is either very dangerous, impractical or impossible, such as radioactive environments, space robotics, and deep space exploration, or where the quick physical transfer of an expert is not preferable or feasible, such as medical telesurgery.

978-1-4673-7509-2/15/$31.00 2015 IEEE

Although a wealth of research regarding teleoperation already exists, a significant amount of it deals with systems-theory aspects of it, and especially the compensation and effects of delay in the control loop, e.g. [1]. Furthermore, although multiple human-machine interfaces have been explored in teleoperation, including exotic modalities such as brain-computer interfacing [2], still an important percentage of the interfaces rely on joysticks, especially in industrial applications. However, despite the amount of research in the aforementioned areas, few frameworks exist towards quantifying human operator performance in teleoperation, such as [3], in which a probabilistic framework aids towards the decomposition of the contributions of correspondence choice [4] and feedback. However, the effects of easy-to-implement feedback mechanisms across various modalities for the case of joystick teleoperation, and most importantly, the basic mechanisms of human operator training, have not yet been adequately studied.

Thus, towards our ultimate goal of creating effective methods for training and assessing human operators of joystick-controlled robots, in this paper we present an extensive study consisting of 18 experimental subjects on simulated as well as 20 on physical robots, using either no feedback or auditory feedback. An important novelty of our study is concerned with the fact that a rich set of multiple observables was recorded towards analysis and evaluation of our main research questions. These include not only joystick and robot angles and timings, but also subjective measures of difficulty, personality and usability data. Furthermore, the experimental setup features a video camera to record the subjects' face to study through automated analysis the facial expressions and blink rate of the subjects; however, this work does not present any results from this study.

In a broader context and in layman's terms, the main initial research questions that we asked are the following: First, how does auditory feedback effect performance and perceived subjective difficulty? Second, what does the perceived difficulty that the subjects experience correlate with? And third, can one devise indicators of operator performance that are easily measurable and which relate strongly to task completion time and to overall accumulated operator experience? However, in order to answer our initial research questions in a tighter context and potential future questions, a carefully designed set of experiments was carried out. Our results provide answers to our main research questions, and also open up exciting avenues for further analysis and investigation.

We will proceed as follows: First, background will be provided for a number of related areas, followed by a detailed exposition of our materials and methods used. Subsequently, results will be presented, followed by a forward-looking discussion, and culminating to our conclusions.

II. Background

Joysticks are often used as input devices to remotely operate a machine, or a robot, in master/slave configuration. Although they have been conceived in the 60s, still they are massively employed in industrial applications. Their supremacy over other input devices (such as hand-based tracking systems [5], datagloves [6] or teaching boxes) is due to the fact that joysticks are reliable, ergonomic (operator's elbows lay on armrests), cost-affordable, ideal for rugged applications and, to a certain extension, intuitive to operate.

Joysticks are used as human-machine interfaces in many commercial applications such as excavators, cranes, forklifts [7], electric-powered wheelchairs [8], robot telemanipulation and micromanipulation [9].

Teleoperating a manipulator, or a slave device, by means of one or more joysticks can be implemented with different control strategies [10]:

- *Direct Rate control*: the manipulator is controlled in such a way that there is a direct correspondence between each joystick DoF and each manipulator joint velocity. In this way the joystick angular position is interpreted as a velocity command for the manipulator joint. Therefore velocity can vary linearly with respect to the joystick position. Typically, this approach is used in excavators or cranes, since the joystick position directly commands the hydraulic valve opening. In fact, there exists a linear relationship between the manipulator joint speed and the valve opening.

- *Resolved Rate Control*: the manipulator is controlled in such a way that there is a direct correspondence between each joystick DoF and spatial DoF of the manipulator. Spatial DoFs are referenced to a convenient coordinate frame. This mapping is intuitive but requires the measurement of the manipulator joint values (feedback) for the interpolation of the joints motions. For this reason, it is implemented mainly in robotic telemanipulation rather than in excavators or cranes.

- *Position Control*: the mapping is between each joystick DoF and each manipulator joint position. Also in this case the slave manipulator is provided with a controller to perform a joint position control, where the input signal is given by the joystick position.

- *Resolved Position Control*: the mapping is between each joystick DoF and spatial DoFs of the manipulator.

The main drawback related to non-resolved controls is due to the fact that mapping between the DoFs of the slave manipulator and the DoFs of joysticks are counterintuitive. This is because the inverse kinematic calculation, from the DoFs of the manipulator to the DoFs of the joystick, is mentally demanding.

The choice of the DoFs mapping affects the overall performance of the manipulator-operator interaction as it has been shown in previous researches. For example, Bock at al. [11] compared different mappings in a 2-D cursor tracking task. In a case, the 2 DoF of the cursor were mapped on a single two-axis joystick. In an other case, they were mapped on a two single-axis joysticks, with different orientations (rotated or in a egocentric frame). As expected, results showed that responses with single-axis joysticks were less accurate, especially when the axes where not oriented egocentrically.

Operation performance of joysticks depends not only on the mapping, but also on many geometric and control parameters, such as length of the joystick handle, control gain [12], and joystick stiffness [13].

Because of the counterintuitive and demanding cognitive mapping processes, candidate users of heavy equipments require long-time training sessions to acquire the skills needed to operate in a safety and efficient way. Training can be performed on the field, an approach that raises several safety and cost issues.

For these reasons in the last decades several training simulators, especially in the field of heavy equipment (excavators and construction equipment), have been developed. Simulators can be classified according to the level of virtual tools they make use of. Typically, the basic configuration of VR(Virtual Reality)-simulators consists in a screen where the virtual equipment is represented and a couple of joysticks [14][15][16]. In more realistic simulators, sound effects [17], virtual reality immersive systems [18] and haptic feedback (provided to the joysticks as well as to the seat [19]) are provided. There exist also AR(Augmented Reality)-simulators where the subject to be trained interacts with a real worksite populated with virtual and real tools [20].

Although several commercial simulators have been produced, as stated by Su et al., a 'proof of the training principles for efficient utilisation of a virtual training systems, especially for operating heavy construction equipment, is still not found in the published literature [21].

The training is usually based on trial-and-error sessions where a skill instructor supervises and gives verbal instructions. Concurred visual and haptic (intended as concurrent augmented haptic) feedback cues are not provided during the training in order to prompt the subjects.

To the best of our knowledge, multiple different kinds of concurrent training cues (audio, haptic or visual) have never been compared as far as teleoperation tasks by means of joysticks are concerned, and most importantly, no clear pattern regarding the relation of reported subjective perceived difficulty of tasks to an absolute easily observable measurement has been yet derived. However, with this work we identify a strong relation that exists between no feedback and auditory

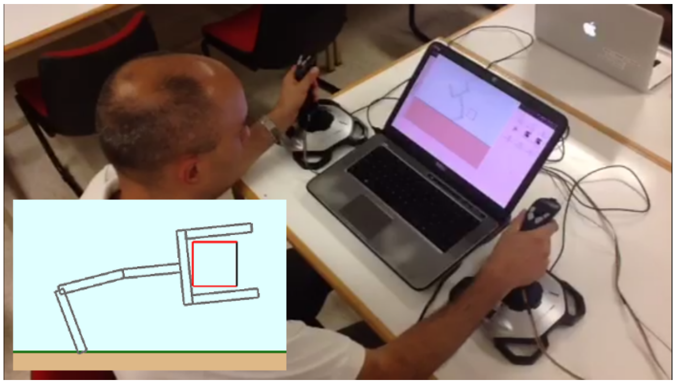

Fig. 1. A subject performing the simulated tele-robotics application using the two joysticks. An acceptable target configuration is shown at the bottom left image.

feedback on teleoperating a simulated robot, which we will empirically justify and discuss.

III. Materials and Methods

The main overall aim of our case study is to increase our knowledge on how humans learn to control physical devices such as excavators and robots through special interfaces, such as joysticks and whole body interfaces, as well as to explore the role of feedback on learner's performance during training through teleoperation applications. In general, feedback is regarded as a critical variable for skill acquisition and is broadly defined as any kind of sensory information related to a response or movement [22]. In our case study we designed an experimental procedure consisting of five sub-experiments. The first four were conducted within a simulation environment, while for the fifth the participants used a physical robotic arm. During the first experiment, the participants were not given a form of feedback during the task execution. The other three groups were given visual, auditory and vibrotactile (haptic) feedback respectively. Here, we report on the initial results of the first two experiments: auditory feedback and no feedback.

A. Simulated teleoperation with a virtual manipulator

The subject, sitting in front of a screen, operates two 4DoFs joysticks (Fig. 1).

The joystick axis position values are used to control a virtual 4 DoFs planar manipulator provided with a gripper (see Fi. 2, left side). The manipulator is controlled in direct rate control mode. The mapping between the speed of the manipulator joint values $\alpha_1, \alpha_2, \alpha_3, c_d$ and the joystick position values J_1, J_2, J_3, J_4 is given as follows

$$\begin{Bmatrix} \dot{\alpha_1} \\ \dot{\alpha_2} \\ \dot{\alpha_3} \\ \dot{c_d} \end{Bmatrix} = \begin{bmatrix} 0 & -1 & 0 & 0 \\ -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 \\ 0 & 0 & -1 & 0 \end{bmatrix} \begin{Bmatrix} J_1 \\ J_2 \\ J_3 \\ J_4 \end{Bmatrix} \quad (1)$$

The virtual environment has been developed in Matlab using the Psychtoolbox. Joystick position values and joints values are saved on a log (on log file for each task) file with a rate of 0.1 sec. The task consists in moving the robot in such a way to grab an oriented square appearing on the screen (see

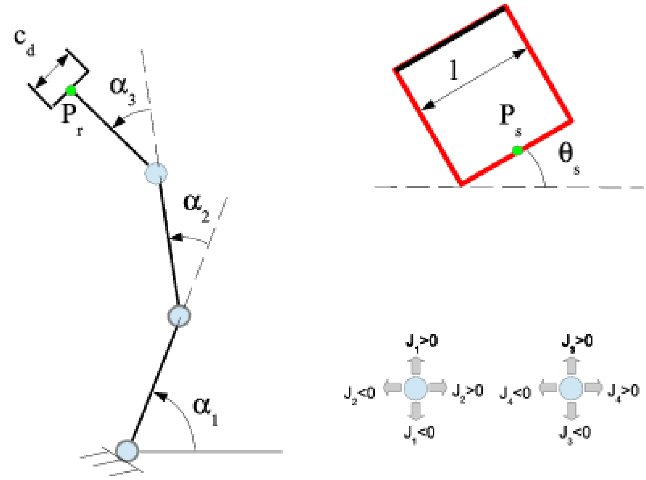

Fig. 2. 4 DoFs simulated manipulator (left side), target square (right, top side) and Joystick values (right, down side))

Fig. 2, right top side). The task is complete when the gripper is almost aligned with the red edges of the target square, namely when

$$\|\mathbf{P}_r - \mathbf{P}_s\| + \chi\,|\alpha_1 + \alpha_2 + \alpha_3 - \theta_s| < \epsilon \quad (2)$$

where ϵ is an error threshold and χ is a parameter introduced to homogenize the error.

B. Feedback Design

The auditory feedback is composed of 30 different tone frequencies and the pitch is a function of the euclidean distance of the gripper from the target location. Starting from low pitch for error actions when the gripper is closer to the target location, the pitch of the auditory feedback is increased ss the errors are performed further away from the target.

C. Teleoperation with a real manipulator

In this section, we introduce the physical robot MERCURY that was used in the physical robot teleoperation experiments. Even though we do not report on the physical robot teleoperation experiments in this work, we believe it is beneficial to describe our complete experimental procedure that would potentially motivate experiment designers reproduce our experiments in the future.

MERCURY robot is a custom built, low-cost, 8-DOF manipulator that was specifically designed for the study of intuitive body-machine interfaces with an ultimate aim to be controlled by brain-machine interfaces. In order to offer a comparative study and further validate our findings with the simulated robot, we have extended our joystick-based interface with MERCURY (shown in Fig. 3). In order to maintain the direct correspondence of the joysticks with the joints of the robots, only 5DOFs are controlled of which the thumb and fingers joints are coupled leaving 4 controllable DOFs in our interface. Hence, the user has access to the shoulder, elbow, wrist and the coupled thumb-fingers joints. The remaining joints were not controllable and were set to angles that would allow the workspace of the real manipulator be as close as

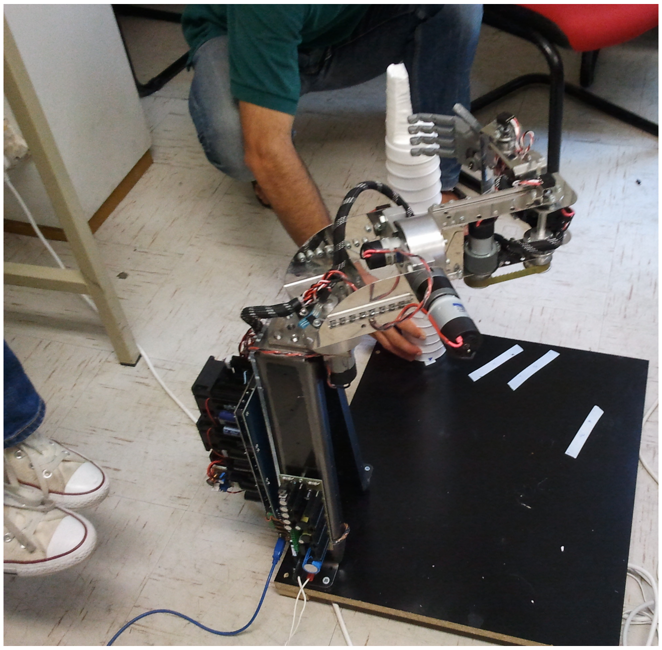

Fig. 3. 4 DoFs are controlled of the 8-DoF manipulator. The subject is asked to grasp the white object in a predefined position and orientation. The experimental subjects are overlooking the robot from above having the same orientation with the manipulator to improve their performance as it was shown from our past experience.

possible to simulated one. Joystick position values and joints values are saved on a log (on log file for each task) file with a rate of 0.1 sec.

Each of the 20 experimental subjects was asked to sit between two joysticks in an elevated position from the robot. The subjects were initially briefed with regards to the task that they have to accomplish, i.e., grasp an object in four possible positions and orientations, with the robot's palm aligned against a flat surface on the object. The completion of the task is either automatically detected from a predefined position of the robot, or is signaled by a experimental supervisor to account for inaccuracies to the target configuration. The experimental subjects were split in two groups of 10 people; the first group received no feedback during the trials and the second group received auditory feedback. At the end of the experiment, the subjects were given a usability test questionnaire to evaluate the user experience.

D. Experimental Procedure

- *Participants* For the simulated robot, data were collected from a total of 18 participant learners during the International Research-Centered Summer School in Cognitive Systems and Interactive Robotics, Data and Content Analysis (http://irss.iit.demokritos.gr/), from 11th to 26th of July 2014, at the Institute of Informatics and Telecommunications (IIT) laboratory at NCSR "Demokritos". There were 5 females (27,8%) and 13 males (72,2%). The average age of students was 27.3 (SD = 5.6). The academic level of the participants was mixed, varying from undergraduate to associate professor. The number of gamers and non-gamers participants was the same (9 gamers, 9 non-gamers).

- *Procedure* Initially we asked the participants to fill in the Big Five Inventory questionnaire [23]. The Big Five factor model of personality is one conceptualization of personality that has been increasingly studied and validated in the scientific literature [24], [25], [26]. According to the Big Five model of personality, these factors are: a) extraversion, b) agreeableness, c) conscientiousness, d) neuroticism and e) openness. The BFI has 44 items to measure personality traits. The five point Likert-type scale with 1 = strongly disagree to 5 = strongly agree was used to measure each item. According to the personality traits analysis for each participant, we formed groups of 9 participants each, for the different phases of our experiment. We wanted each group to have similar distribution of personalities with the other groups (equivalent/ balanced groups). We also wanted the number of females in each group to be the same (if possible).

During each phase of the experiment, each group was given 9 tasks of scaled difficulty (3 easy, 3 medium, 3 hard) to complete. In each task, the goal was to grip a square target object that appears on a screen with the gripper of a simulated robotic arm. One such task is shown in Fig. 1. Before considering the difficulty of each task, we asked 5 other randomly selected people to try to accomplish 12 tasks and tell us their perceptions of difficulty for each one of them. Based on these perceptions and the respective times to complete the tasks, we initially estimated the actual difficulty of the tasks. Three of the initial tasks were excluded from the final procedure because they were considered as outliers. Furthermore, before taking the tasks, we gave to the participants a short briefing. The briefing would supply them with the necessary instructions and guidance throughout the procedure, by explaining shortly the goals and the overall process.

During the simulation activity, we provided to the participants a sequence of tasks and asked them to guide a simplified simulation of an excavator. In each task, the goal was to grip the square target object that appears on the screen in different initial positions. The excavator was made up of three links plus a gripper. In our case, the simulated robot had four angles that could be rotated: three for each one of the excavator's links, and one for the gripper. In order to complete the tasks, the participants should take care of the orientation of the gripper: the three red edges of the square target object should be aligned with the gripper surface, as shown in the diagram (gripper picture). To control the simulated robot, the participants were given two joysticks. They had to figure out on their own which was the mapping between the joystick and the excavator movements. During the experiments, the tasks' order of appearance was not randomized, but pre-determined according to a cycling iteration protocol in order to maintain the balanced design of the procedure. After completing all tasks, the participants from the feedback sub-groups were asked 5 questions regarding their perceptions of the effectiveness of feedback. All questions were in Likert-scale 1=strongly disagree to 7=strongly agree. For the purpose of our case study, we also implemented an overall usability evaluation questionnaire. The questionnaire consisted of 28 questions and was build upon the CBAAM, proposed in [6]. The questions were selected to measure the following categories: a) ease of learning, b) perceived ease of use, c) perceived playfulness, d) perceived usefulness, e) satisfaction. Each one of these categories included different items/factors. To measure these items, we used the seven point Likert-type scale with 1 = strongly disagree to 7 = strongly agree [27]. The simulation environment was build on a MacBook using Matlab, while for the questionnaires we used googleforms.

Facial Expressions and Blink Rate: A front facing color camera with resolution 1280 x 1024 at 27 frames per second was used to record a video of each subject's facial expressions while they sat the experiment. Each video was processed using the Fraunhofer SHORE facial analysis system [28] and intermediate data was obtained on the subject's emotional state as portrayed through their facial expressions for each trial and experiment. The data comes in the form of zero to 100% ratings for four dimensions of human operator affect: happiness, sadness, anger, and surprise. Each video was also processed to obtain blink detection as a measurement for each user, trial, and experiment. This was chosen as blink rate is known to be corellated with user engagement in a task [29].

IV. Results

Our initial results are concerned with answers to the following three research questions: First, how does auditory feedback effect performance and subjective reported difficulty? Second, and most importantly, what does the reported difficulty that the subjects experience correlate with? And third, can one devise indicators of operator performance that are easily measurable and which relate strongly to task completion time and to overall accumulated operator experience?

Let us examine these questions in turn:

A. Auditory Feedback vs. No Feedback

First, we examined the mean task times per subject, for the cases of auditory feedback versus no feedback. Fig. 4 shows the boxplots of mean times, which had the following statistics: No Feedback (mean = 144sec, median = 133sec, std = 76sec), Auditory Feedback (mean = 121sec, median = 101sec, std = 61sec). Although it seems that auditory feedback decreases the mean, the median, as well as the variance of time, this cannot be supported with statistical significance from our empirical data, thus not further supporting [30]. A Kolmogorov-Smirnov test verified normality for both no-feedback as well as auditory-feedback total times per subject, but two-sample t-test for means (P=0.49), Wilcoxon-rank for medians (P=0.86), as well as F-tests (P=0.55) for equal variance all failed to give statistically significant results.

Then, we examined the mean subjective reported difficulty per subject, for the cases of auditory feedback versus no feedback. Fig. 5 shows the boxplots of means of subjective reported difficulties, which had the following statistics: No Feedback (mean = 3.125, std = 0.605), Auditory Feedback (mean = 2.815, std = 0.272). However, here we can indeed support with statistical significance that the variance of subjective reported difficulty decreases with auditory feedback. A Kolmogorov-Smirnov test verified normality for both no-feedback as well as auditory-feedback reported difficulties, and an F-test proved that the variance for the case of auditory feedback is less (with a ratio estimate of around 2.2), with $P<0.05$ (0.0366).

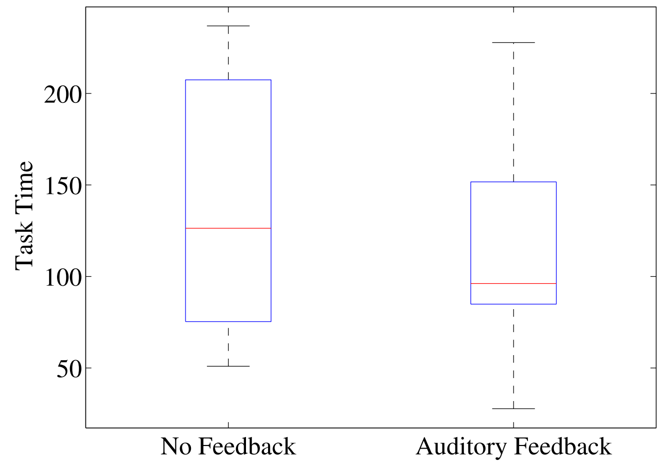

Fig. 4. Mean task time per subject depending on feedback

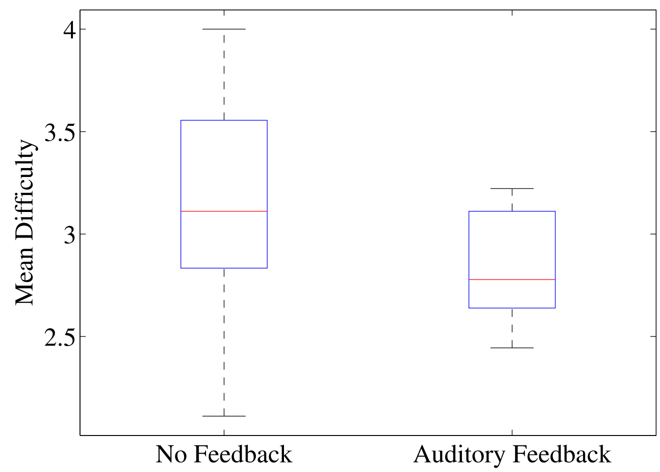

Fig. 5. Mean subjective reported difficulty per subject depending on feedback

B. Subjective Difficulty vs. Task Time

Fig. 6 shows the times required to complete each task versus the perceived difficulty of the task in a semilogarithmic plot. A linear regression gives the fitting line: log10(time) = 0.27*difficulty + 1.1, with an R-squared value of 0.53. Higher-order polynomials give a very small increase in the explanation of variance (0.56 for quadratic and cubic), and thus the linear fit provides a very good approximation without overfitting. Most importantly, there are similarities with the WeberFechner law: subjective the perceived intensity is related to the logarithm of the objective magnitude. In our case, the subjective perceived difficulty is related to the logarithm of the total time required to finish the task.

C. Error Types

Multiple qualitatively different categories of operator errors can be postulated, given our observations. Furthermore, the distribution of these errors changes with operator experience. Three of the most frequently found categories are the following:

1) Controller Polarity Mismatch: The operator's desired direction of move of joint angle is opposite to the effect of

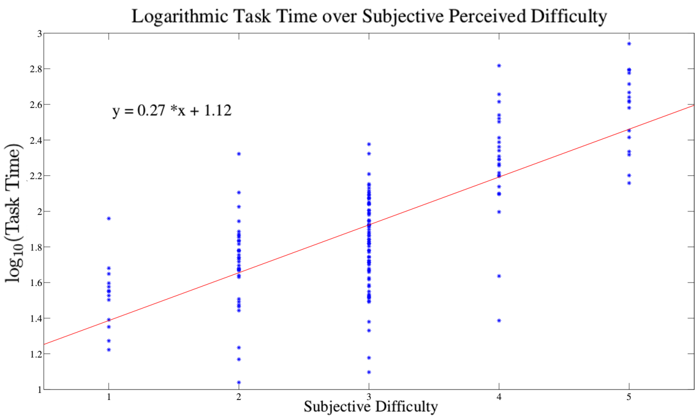

Fig. 6. Semilogarithmic plot of task time versus subjective perceived difficulty.

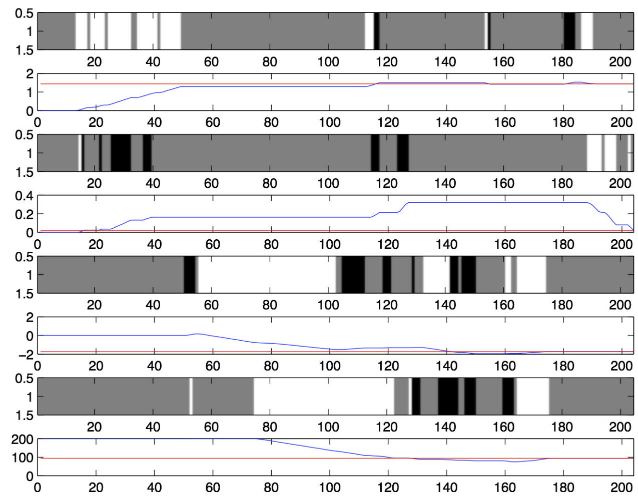

Fig. 7. How the CWJR of a single subject over a single task is calculated: The area of the white segments is added (i.e. total time joystick is pointing to the right direction towards the goal set point of the joint angle), and divided with the total area of the black segments (i.e. total time joystick is pointing to the wrong direction towards the goal set point of the joint angle). The grey segments correspond to times where that specific joystick axis is centered (zero angle).

the attempted direction of the joystick, causing the robot to move to the wrong direction as compared to the direction that would bring the joint angle towards the desired setpoint.

2) Controller Axis to Joint Mismatch: The operator's desired robot joint to be moved is different than the actual effected joint of the robot, causing the robot to often move to the wrong direction as compared to the direction that would bring the joint angle towards the desired setpoint.

3) Controller Overshoot Error: The operator reaches the desired setpoint, but continues moving beyond the setpoint, usually necessitating a subsequent reversal of joystick polarity towards a corrective move.

4) Controller Redundant Axis Error: The operator moves both axis of a single joystick, while only paying attention to one.

5) Purposeless General Motion Error: The operator moves around the joysticks in a purposeless way, usually apparently randomly or circularly changing axis and positions, often out of frustration or helplessness.

D. Indicators of Operator Performance

Here, our main question is: can one devise indicators of operator performance that are easily measurable and which relate strongly to task completion time and to overall accumulated operator experience? Such indicators can be quite useful, as they can be potentially estimated by observing the operator for a relatively short time period, and then they can act as rough predictors of his experience and of the task completion time. Let us introduce two such indicators, and examine the resulting relations.

1) Correct-to-Wrong Ratio (CWJR): An important indicator that we are proposing is the time ratio of the Correct joystick directions versus the Wrong joystick direction. This is calculated in the following way: For each trial, we calculate the time that the joystick is actively pointing towards the correct direction with respect to reaching the setpoint of a specific joint angle, divided by the time the joystick is pointing towards the wrong direction.

An illustration of this can be seen in Fig. 7, for the example case of a trial of one of our subjects, which is actually the case of quite a competent subject. Eight horizontal lines can be seen, in four pairs of two, which each pair describing activity for a single joystick-robot joint axis. The uppermost timelines of the pairs contain segments of three colors: grey, white, and black. Grey segments correspond to no joystick activity for the specific axis, the white segments correspond to joystick movement towards the correct direction in order to reach the setpoint, and black segments to joystick movement in the wrong direction. The lower timeline of each of each pair corresponds to the current joint angle (in blue) and the setpoint of the angle required for reaching the goal (horizontal red line). CWJR is the ratio of the white areas in the upper timelines divided by the black areas.

Fig. 9 shows the normalized relation between the logarithm of CWJR and the logarithm of total task time, revealing the law connecting the two is a power law. Concretely, the linear regression gives the fitting line: log2(Median(CWJR)) = -0.33*log2(TotalTaskTime) + 4, with an R-squared value of 1.5205. For comparison, the next order polynomial, i.e., the quadratic regression, presents only a low decrease in R-squared value to 1.5198. Furthermore, Fig. 8 illustrates the linearly increasing trend of CWJR as the experience of the operator increases.

2) Average Velocity of Robot Joints (AVRJ): Yet another important indicator that we are proposing is the Average Velocity of the Robot Joints. This was strongly related to user experience and task time too. Specifically, this indicator increases as user experience increases (Fig. 10), and the logarithm of AVRJ decreases with the logarithm of task time, implying a power law relation (Fig. 11).

V. FUTURE DIRECTIONS

In addition to the initial results presented above, our rich acquired dataset which affords the examination of numerous other interesting research questions: First, comparison of the

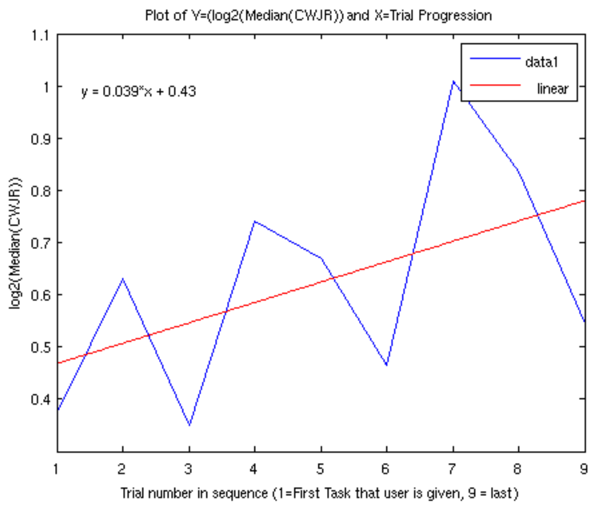

Fig. 8. CWJR is being improved as the user is building experience over tasks. Notice the triplet pattern, arising from the sequence of difficulty of tasks: {1=Easy, 2=Medium, 3=Hard, 4=Easy, 5=Medium, 6=Hard, 7=Easy, 8=Medium, 9=Hard}.

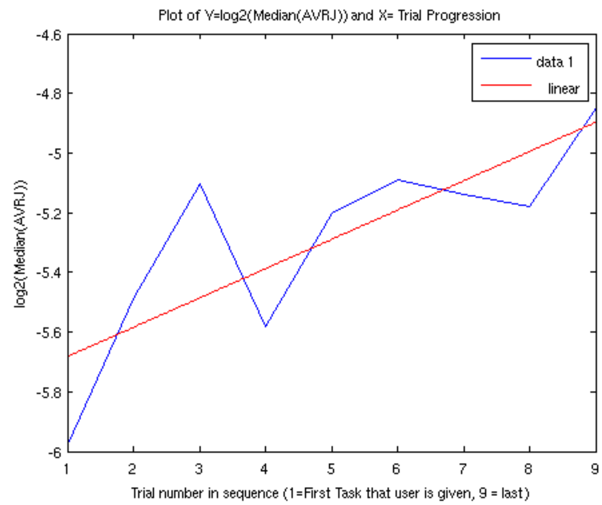

Fig. 10. AVRJ is also being improved as the user is building experience over tasks. Again, notice the triplet pattern, arising from the sequence of difficulty of tasks: {1=Easy, 2=Medium, 3=Hard, 4=Easy, 5=Medium, 6=Hard, 7=Easy, 8=Medium, 9=Hard}.

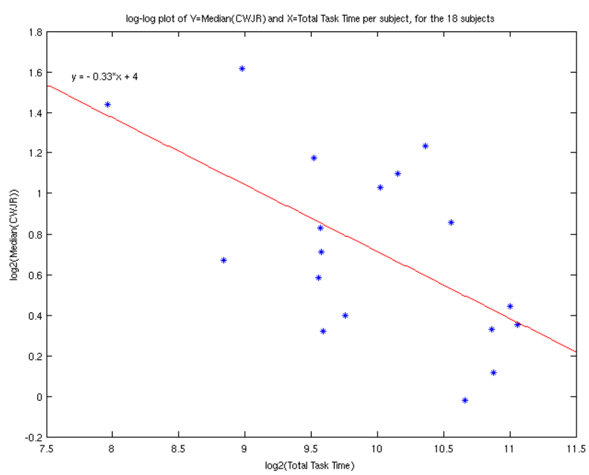

Fig. 9. Log-Log Relation of median (CWJR) vs. total task times per subject

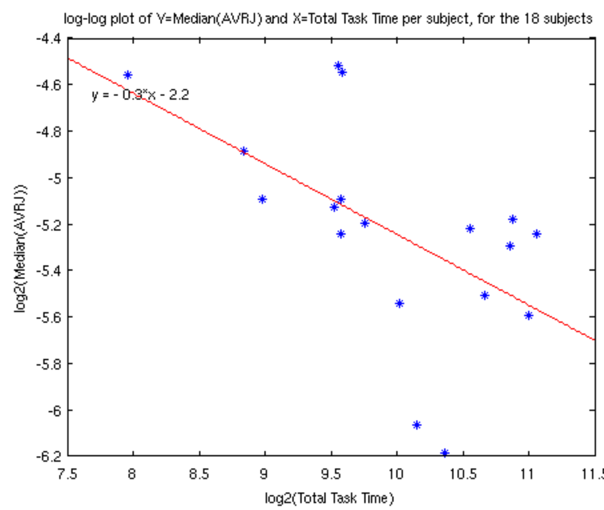

Fig. 11. Log-Log Relation of median (AVRJ) vs. total task times per subject

simulator results with the physical robot results. Second, a quantification and examination of the distribution of the four error types across subjects, experience, and difficulty is underway. Third, further study and validate indicators proposed by other research groups followed by comparisons with the proposed ones in this work. Fourth, attempts towards automatic recognition of errors, and provision of more multi-faceted feedback are in progress. Fifth, there are a lot of interesting patterns that have started to appear upon our initial examination of the relation between teloperation performance, personality and emotion, as assessed by the big-five questionnaire and the fraunhofer SHORE automated facial expression analyzer. Sixth, and most important, we are currently devising algorithms for adaptive personalization of training sequences towards maximizing performance while minimizing training time. And the above are just an initial set of potential directions that are already afforded by the collected data, towards creating effective training and assessment of joystick-teleoperated robots.

VI. Conclusion

Towards our ultimate goal of creating effective methods for training and assessing human operators of joystick-controlled robots, in this paper we investigated our three initial reseach questions. Specifically, we designed an extensive study consisting of 38 experimental subjects on both simulated as well as physical robots, using either no feedback or auditory feedback. In this paper we report on initial results based on analysis of the first 18 subjects, belonging to auditory feedback and no feedback subgroups, on the simulated robot. Multiple observables were recorded, including not only joystick and robot angles and timings, but also subjective measures of difficulty, personality and usability data, and automated analysis of facial expressions and blink rate of the subjects.

Our initial results support the following answers to the research questions that we posed: First, that auditory feedback cannot yet be proven on the basis of our data to be more effective than no feedback. However, the variance of subjective reported difficulty when auditory feedback exists can be proven to be less with statistical significance, as compared to the variance of subjective reported difficulty when there is no feedback. Second, and quite importantly, it was found that the subjective difficulty of a task is linearly related with the logarithm of total task time. Third, we introduced two important indicators of operator performance, namely the Average Velocity of Robot Joint (AVRJ), and the Correct-to-Wrong-Joystick Direction Ratio (CWJR), and we showed how these relate to accumulated user experience and with task time. It is worth noting though that these results have been obtained by controlling a simulated robot based on Direct Rate Control and it would be risky to generalize them in the other control strategies (Section II) of joystick-based teleoperated robots.

Finally, we provided a concrete progression of future work in a forward-looking discussion. Thus, through all the above, we have provided a contribution towards our ultimate goal of effectively training and assessing human operators of joystick-controlled robots, supporting a wealth of applications across a range of domains, and thus bringing tele-robotics closer to our everyday life for the benefit of humanity.

Acknowledgment

This work has been supported by “IRSS - International Research-Centered Summer School in ‘Cognitive Systems and Interactive Robotics, Social Media, Digital Preservation’”.

References

[1] T. B. Sheridan, “Space teleoperation through time delay: review and prognosis,” *Robotics and Automation, IEEE Transactions on*, vol. 9, no. 5, pp. 592–606, 1993.

[2] C. Christoforou, N. Mavridis, E. L. Machado, and G. Spanoudis, “Android tele-operation through brain-computer interfacing: A real-world demo with non-expert users,” in *Proceedings of the International Symposium on Robotics and Intelligent Sensors (IRIS)*, 2010.

[3] N. Mavridis, N. Giakoumidis, and E. L. Machado, “A novel evaluation framework for teleoperation and a case study on natural human-arm-imitation through motion capture,” *International Journal of Social Robotics*, vol. 4, no. 1, pp. 5–18, 2012.

[4] A. Alissandrakis, C. L. Nehaniv, and K. Dautenhahn, “Correspondence mapping induced state and action metrics for robotic imitation,” *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 37, no. 2, pp. 299–307, 2007.

[5] C. Guerrero-Rincon, A. Uribe-Quevedo, H. Leon-Rodriguez, and J.-O. Park, “Hand-based tracking animatronics interaction,” 2013.

[6] M. Liarokapis, P. Artemiadis, and K. Kyriakopoulos, “Mapping human to robot motion with functional anthropomorphism for teleoperation and telemanipulation with robot arm hand systems,” 2013, p. 2075.

[7] K. Yuen, S. Choi, and X. Yang, “A full-immersive cave-based vr simulation system of forklift truck operations for safety training,” *Computer-Aided Design and Applications*, vol. 7, no. 2, pp. 235–245, 2010.

[8] H. Caltenco, B. Breidegard, B. Jonsson, and L. Andreasen Struijk, “Understanding computer users with tetraplegia: Survey of assistive technology users,” *International Journal of Human-Computer Interaction*, vol. 28, no. 4, pp. 258–268, 2012.

[9] L. Mattos, E. Grant, R. Thresher, K. Kluckman, and D. Caldwell, “Experiments with a teleoperated system for improved bio-micromanipulations,” 2010, pp. 1–6.

[10] J. Draper, *Teleoperator hand controllers: A contextual human factors assessment*, 1994.

[11] O. Bock, C. Worringham, and S. Dawson, “On the use of different spatial reference frames for movement control,” *Motor Control*, vol. 13, no. 1, pp. 43–53, 2009.

[12] M. Huysmans, M. de Looze, M. Hoozemans, A. van der Beek, and J. van Dieen, “The effect of joystick handle size and gain at two levels of required precision on performance and physical load on crane operators,” *Ergonomics*, vol. 49, no. 11, pp. 1021–1035, 2006.

[13] M. Oliver, R. Rogers, J. Rickards, M. Tingley, and E. Biden, “Effect of stiffness and movement speed on selected dynamic torque characteristics of hydraulic-actuation joystick controls for heavy vehicles,” *Ergonomics*, vol. 49, no. 3, pp. 249–268, 2006.

[14] T. Ni, H. Zhang, C. Yu, D. Zhao, and S. Liu, “Design of highly realistic virtual environment for excavator simulator,” *Computers and Electrical Engineering*, vol. 39, no. 7, pp. 2112–2123, 2013, cited By (since 1996)0.

[15] H. Zhang, C. Yu, D. Zhao, and T. Ni, “Visual simulation for hydraulic excavator based on virtual reality,” *Huazhong Keji Daxue Xuebao (Ziran Kexue Ban)/Journal of Huazhong University of Science and Technology (Natural Science Edition)*, vol. 41, no. 3, pp. 87–91, 2013.

[16] M. Gonzalez, A. Luaces, D. Dopico, and J. Cuadrado, “A 3d physics-based hydraulic excavator simulator,” 2009, pp. 75–80, cited By (since 1996)0.

[17] G. Lee, S. Im, and E. Kim, “Development of an excavator simulator for an inteligent excavating system,” 2011, pp. 1445–1448, cited By (since 1996)0.

[18] B. Patrao and P. Menezes, “An immersive system for the training of tower crane operators,” 2013, pp. 158–159.

[19] X. Wang, P. Dunston, R. Proctor, L. Hou, and J. So, “Reflections on using a game engine to develop a virtual training system for construction excavator operators,” 2011, pp. 631–636.

[20] X. Wang and P. Dunston, “Design, strategies, and issues towards an augmented reality-based construction training platform,” *Electronic Journal of Information Technology in Construction*, vol. 12, pp. 363–380, 2007.

[21] X. Su, P. Dunston, R. Proctor, and X. Wang, “Influence of training schedule on development of perceptual-motor control skills for construction equipment operators in a virtual training system,” *Automation in Construction*, vol. 35, pp. 439–447, 2013.

[22] D. M. Wolpert, “Probabilistic models in human sensorimotor control,” *Human Movement Science*, vol. 26, no. 4, pp. 511–524, 2007.

[23] O. P. John and S. Srivastava, *Handbook of Personality: Theory and Research*, 1999.

[24] M. C. N. Terzis, V. and A. A. Economides, “How student’s personality traits affect computer based assessment acceptance: Integrating bfi with cbaam,” *Computers in Human Behavior*, vol. 28, no. 5, pp. 1985–1996, 2012.

[25] S. S. Lakhal, S. and E. Frenette, “Personality and preference for evaluation methods: a study among business administration students,” *Studies In Educational Evaluation*, vol. 39, no. 2, pp. 103–115, 2013.

[26] F. A. D. G. Chamorro-Premuzic, T. and P. Heaven, “Personality and preference for academic assessment: A study with australian university students,” *Learning and Individual Differences*, vol. 15, no. 4, pp. 247–256, 2005.

[27] V. Terzis and A. A. Economides, “The acceptance and use of computer based assessment,” *Computers and Education*, vol. 56, no. 4, pp. 1032–1044, 2011.

[28] T. Ruf, A. Ernst, and C. Küblbeck, “Face detection with the sophisticated high-speed object recognition engine (shore),” in *Microelectronic Systems*. Springer, 2011, pp. 243–252.

[29] S. Chen, J. Epps, N. Ruiz, and F. Chen, “Eye activity as a measure of human mental effort in hci,” in *Proceedings of the 16th international conference on Intelligent user interfaces*. ACM, 2011, pp. 315–318.

[30] M. K. Apostolos, H. Zak, H. Das, and P. S. Schenker, “Multisensory feedback in advanced teleoperations: benefits of auditory cues,” vol. 1828, 1993, pp. 98–105.