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On the subjective difficulty of Joystick-based robot arm teleoperation with auditory feedback

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***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, in this paper we present an extensive study consisting of 18 experimental subjects controlling a simulated robot, using either no feedback or auditory feedback. 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, and second, that the subjective difficulty of a task is linearly related with the logarithm of task completion 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.

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 controlling a simulated robot, 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, and automated analysis of facial expressions and blink rate of the subjects.

The main initial research questions that we asked are, in layman's terms, the following: First, how does auditory feedback effect performance and perceived subjective difficulty? And second, and most importantly, what does the perceived difficulty that the subjects experience correlate with?

In order to answer our initial research questions 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 extent, 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. Previous research, Bock *et 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 one 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 safe 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 of a screen where the virtual equipment is represented and a couple of joysticks [14]–[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 utilization 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 skilled 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 and easily observable measurement has been yet derived. However, as we shall see in this paper, a strong relation exists, 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, i.e., auditory feedback and no feedback on the simulated robot.

A. *Simulated teleoperation with a virtual manipulator*

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

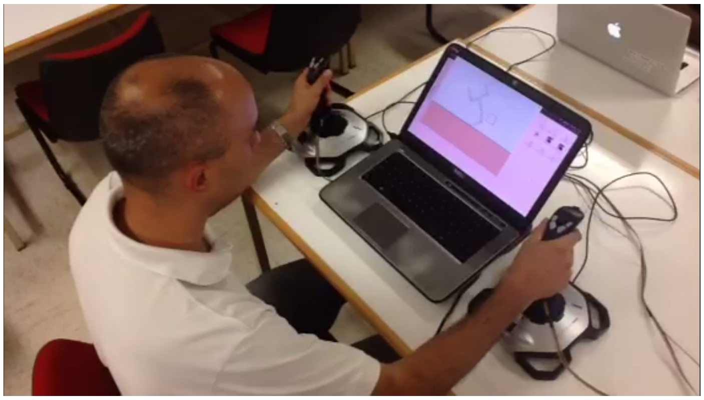

Fig. 1. A subject performing the simulated telerobotics application using the two joysticks

The joystick axis position values are used to control a virtual 4 DoFs planar manipulator provided with a gripper (Fig. 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

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

The virtual environment has been developed in Matlab using *Psychtoolbox* [23]. Psychtoolbox is an open source Matlab/Octave library that provides a simple programming interface to vision and neuroscience researchers. Psychtoolbox is optimized towards developing simulators or computational experiments that need to present accurately controlled visual and auditory stimuli, e.g., for Psychophysics and Psychology experiments. Joystick position values and joints values are saved on a log (a log file for each task) file with a sampling rate of 10Hz. The task consists in moving the robot in such a way to grab an oriented square appearing on the screen (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

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

where $\mathbf{P}_r$ is the current position of the end-effector including the length c_d of the clamp, $\mathbf{P}_s$ is the target position of the square including the length l of this particular task, α_i is the joint angle of link i, α_s is the angle of the target location. Fig. 2 presents visually the aforementioned parameters. Finally, 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 starting from low pitch for error actions when the gripper is closer to the setpoint. The pitch of the auditory feedback is increased as the gripper moves away from the target.

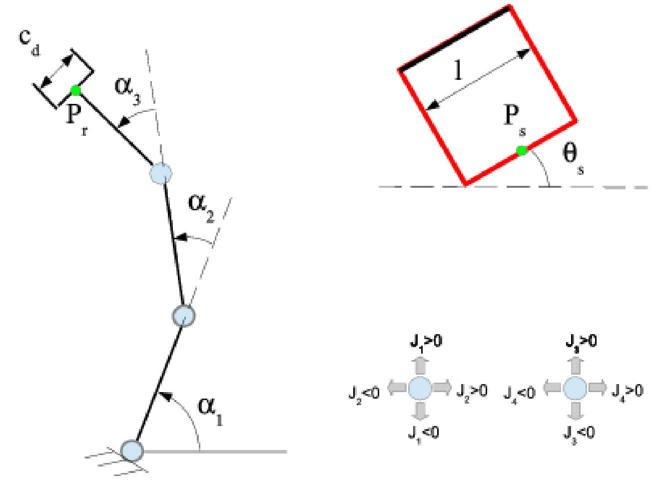

Fig. 2. 4 DoFs simulated manipulator (left side), target square (right, top side) and Joystick values (right, down side))

C. Experimental Procedure

- *Participants:* 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 [24]. The Big Five factor model of personality is one conceptualization of personality that has been increasingly studied and validated in the scientific literature [25]–[27]. 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. 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. For each task the user was responsible to move the robot in a configuration that would grab the oriented square with the gripper on the screen. The required robot configuration to achieve the task relies on the pose of the target square. Hence, an easy task would require for example only a single joint to rotate from the initial configuration, however, other tasks might require all joints to reach a non-obvious configuration to appropriately approach and orient with the square. By uniformly distributing the squares on the workspace for the 12 tasks, our aim was to cover as much as possible the required effort put from each subject for each task, while keeping the experiment interesting and avoiding frustration to first-time users. 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 the participants ran through the tasks, we provided them 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 joints that could be controlled: three rotational 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 (Fig. 2). 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 subgroups were asked 5 questions regarding their perceptions of the effectiveness of feedback. All questions were in Likert-scale, with 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 [28]. 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" [28]. The simulation environment was built 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 [29] 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 correlated with user engagement in a task [30].

IV. RESULTS

Our initial results are concerned with answers to the following two research questions: First, how does auditory feedback effect performance and subjective reported difficulty? And second, and most importantly, what does the reported difficulty that the subjects experience correlate with?

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. 3 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 [31]. 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.

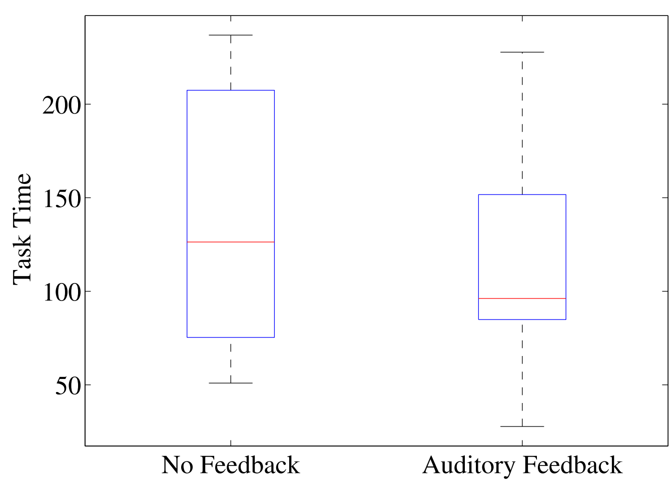

Fig. 3. Mean task time per subject depending on feedback

Then, we examined the mean subjective reported difficulty per subject, for the cases of auditory feedback versus no feedback. Fig. 4 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. Initially, a Kolmogorov-Smirnov test verified normality for both no-feedback as well as auditory-feedback reported difficulties. The two sample F-test is used to determine whether the variance of two populations are equal. In this experiment, the F-test proved that the variance for the case of auditory feedback is less (with a ratio estimate of around 2.2) at the 5% significance level with $P<0.05$ (0.0366).

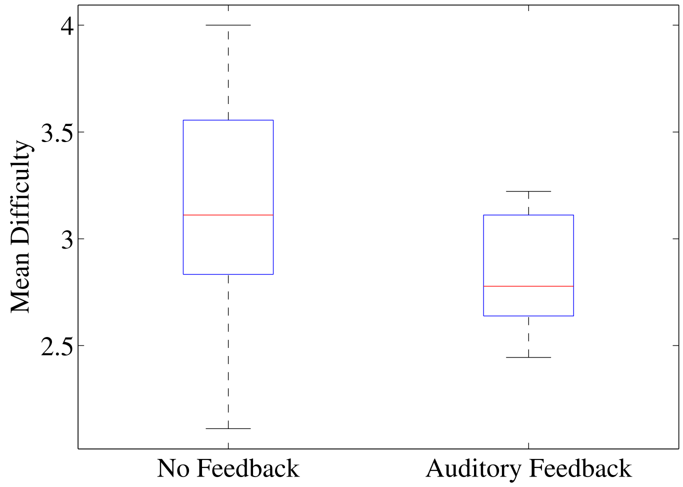

Fig. 4. Mean subjective reported difficulty per subject depending on feedback

B. Subjective Difficulty vs. Task Time

Fig. 5 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: $\log_{10}(time) = 0.27 \times difficulty + 1.12$, 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 Weber–Fechner 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.

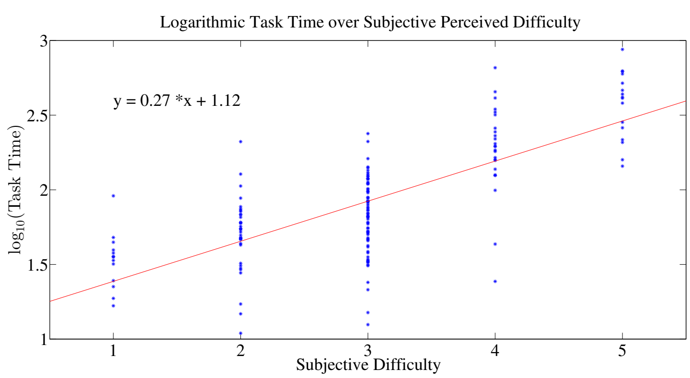

Fig. 5. Semilogarithmic plot of task time versus subjective perceived difficulty

V. Discussion

In addition to the initial results presented above, our rich acquired dataset affords the examination of numerous other interesting research questions: First, examination of the other two types of feedback that were implemented, i.e. visual and haptic. Second, comparison of the simulator results with the physical robot results. Third, proposal and evaluation of highly-predictive measures of future performance and operator competence. Fourth, the taxonimization of different types of operator errors during teleoperation. Fifth, a quantification and examination of the distribution of the four error types across subjects, experience, and difficulty is underway. Attempts towards automatic recognition of errors, and provision of more multi-faceted feedback are in progress. Sixth, 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. Seventh, 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 the following two initial questions, in laymans terms: First, how does auditory feedback effect performance and subjective reported difficulty? And second, and most importantly, what does the reported difficulty that the subjects experience correlate with?

Towards answering these questions, we designed an extensive study consisting of 45 experimental subjects on both simulated as well as physical robots, using three different types of feedback: visual, auditory, and haptic. In this paper we report on initial results based on analysis of the first 18 subjects, belonging to auditory feedback and no feedback subgroups. 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 (Fig. 6) 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 for teleoperation learning. 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. 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 telerobotics closer to our everyday life for the benefit of humanity.

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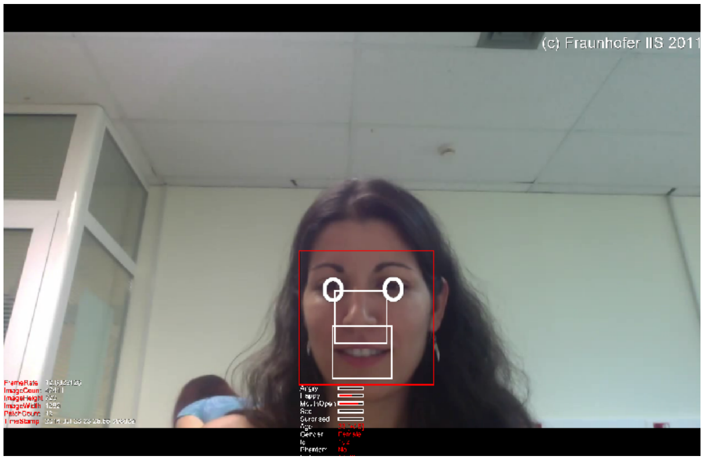

Fig. 6. A subject performing the simulated telerobotics application with visual feedback. The subject's facial expressions were analysed for further analysis in the future.

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