Sensing the partner: toward effective robot tutoring in motor skill learning

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Abstract. Effective tutoring during motor learning requires to provide the appropriate physical assistance to the learners, but at the same time to assess and adapt to their state, to avoid frustration. With the aim of endowing robot tutors with these abilities, we designed an experiment in which participants had to acquire a new motor ability - balancing an unstable inverted pendulum - with the support of a robot providing fixed physical assistance. We analyzed participants' behavior and explicit evaluations to (i) identify the motor strategy associated with best performances in the task; (ii) assess whether natural facial expressions automatically extracted from cameras during task execution can inform about the participant's state. The results indicate that the variation and the mean of the wrist velocity are the most relevant in the effective balancing strategy, suggesting that a robot tutor could reorient the attention of the pupil on this parameter to facilitate the learning process. Moreover, facial expressions vary significantly during the task, especially in the dimension of Valence, which decreases with training. Interestingly, only when the robot had an anthropomorphic presence, Valence correlated with the degree of frustration experienced in the task. These findings highlight that both physical behavior and affective signals could be integrated by an autonomous robot to generate adaptive and individualized assistance, mindful both of the learning process and the partner's affective state.

Keywords: Social Robot Tutor · Motor Skill Learning · Multimodal Assistance.

1 Introduction

The acquisition of qualified motor skills is crucial in human daily and professional life. The role of the expert tutor in the skill transfer process is of critical importance and often relays on a series of implicit signals in which several communication channels are involved. Indeed, the interaction between the expert and the learner could be seen as a continuous flow of physical and affective, social signals, which lead the tutor to build a complex and complete model of the pupil's skills and state and to act accordingly. This is what happens, for example, when a physiotherapist trains a patient to recover certain motor skills. Beyond the selection of the appropriate force and physical assistance to support the learning, the expert physiotherapists are mindful of the state of their patients. They aim at keeping the patients committed to the task, but at the same time, they monitor the stress, anger, or other negative reactions that might be triggered by the lengthy and often challenging rehabilitation process. Given the widespread adoption of robotics in the context of rehabilitation [8], it would be desirable that also robot tutors would exhibit a similar ability of understanding and adapting to the learner's needs both from the physical and the affective perspectives. In the field of motor skill learning, many researchers have focused mostly on physical interactions between humans and robots to define the optimal training strategy [7, 14]. On the other hand, several studies have demonstrated the potential of social robots to positively contribute to users' learning and experience in the field of skill acquisition [5, 13]. Also, it has been shown that the presence of physical robots may have advantages in sensing and using affective data, by inducing higher degrees of emotional expressiveness [12]. These results suggest not only that embodied social robots may be a more effective medium for developing intelligent tutoring systems, but also that integrating affect-awareness in the tutoring model can lead to important benefits. We state that, for motor learning to be effective and to optimize the experience of the human naive, social robot tutors should integrate into their decision-making process physical and performance-related information with social and affective cues. However, works that focus on the relative roles of the physical and the social components in a single, unified setting are still scarce. The design of an optimal assistive architecture for social robots is an open challenge that implies facing different aspects. Indeed, before implementing the robot tutoring behavior, it is necessary to (1) understand the effect of the physical presence of the social robot as an expert trainer on the performance and experience of the subjects, and (2) identify the most informative cues that the robot has to exploit in order to decide the best way to assist the learner. In the current work, we present a novel experimental design in which naive participants had to learn the right strategy to accomplish a complex motor task, i.e. stabilizing an inverted pendulum by using a robotic manipulandum, the Wristbot [9, 8]. We ran a between-subjects study: participants of both groups performed the training with physical assistance that facilitated the task in the same way. However, while for the *Control group* the assistance was attributed to the Wristbot, for the *iCub group* the humanoid robot iCub [10] pretended to provide the assistance. In doing so, it exhibited some social behaviors (as gazing and talking) and played the role of the expert tutor. In a previous study [4], we reported the effect of the presence of the humanoid social robot embodying the physical assistance on the performance and the self-reported experience of the naive learners, addressing the first of the above-mentioned issues. We observed that people who interacted with the humanoid robot iCub reported a more enjoyable training experience, without negative effects on attention and effort levels. Also, for both groups, the training was effective, with significant improvements in performance in the test phase. In light of the results obtained, in this study we want to address the second main question and deepen the understanding of the relative role of the different physical and social cues directly detectable by the robot and their potential use in the tutoring interaction. In particular, we addressed the following research questions: i) concerning the physical cues, we are interested in investigating which are the most significant features of participants' motion that differentiate a successful from an unsuccessful strategy. A robot tutor endowed with such information could guide the learner's attention to selectively focus on the most relevant motion properties to facilitate the training; ii) in the context of affective cues analysis, we tested if it was possible to infer the users' state starting from implicit affective signals (like Arousal and Valence) computed from the participants' facial expressions, by comparing them with the self-reported judgments obtained through questionnaires. Moreover, we evaluated whether and how the presence of the social humanoid tutor changed the communicative behavior of the naive subjects.

2 Methods

2.1 Participants

We recruited 32 participants (18 females, 14 males). Half of the subjects were tested in the *Control group* (9 females, 7 males, 26.1±3.9 years of age), and the remaining were tested in the *iCub group* (9 females, 7 males, 27.1±3.1 years of age). All participants gave their written informed consent before participating in the study. They were right-handed and did not have any known neurological or physical impairment. The research was approved by the local ethical committee of the Liguria Region (n. 222REG2015).

2.2 Experimental Setup

The setup comprised the inverted pendulum structure, a robotic manipulandum (the Wristbot), and, for the *iCub group*, also the humanoid robot iCub. The pendulum structure was composed of a table on which an inverted motorized pendulum was fixed. The pendulum was made of a carbon fiber rod 52 cm long, linked on its basis to a brushless motor. The pendulum had a maximal angular excursion of ±40 degrees. During the task, participants sat on a fixed chair in front of the pendulum structure, holding with their right hand the Wristbot handle (Fig. 1, right panel) that worked as a haptic joystick to deliver forces directly to the pendulum and control its position. For this specific task, the Wristbot allowed only movements on the prono-supination plane of the human wrist, with a maximal angular displacement of ±60 degrees. A high-resolution RGB camera was placed on the opposite side of the pendulum structure, recording the facial expressions of participants for subsequent offline analysis. On the same side, for the *iCub group*, the humanoid robot stood on a fixed platform facing the participant. A one-meter sided squared surface covered the pendulum structure and the hands of both the subject and the robot (Fig. 1, left panel).

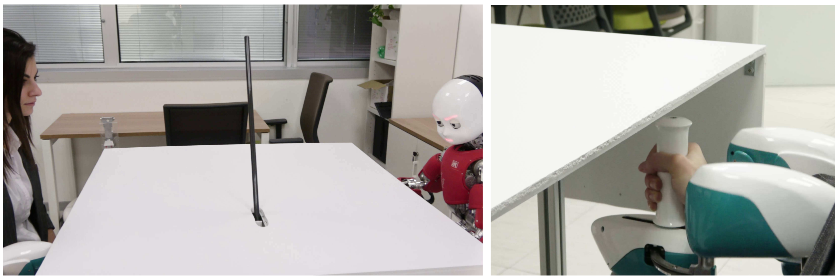

Fig. 1. In the left panel, the robot iCub and the participant facing each other on the opposite sides of the pendulum structure while performing the task in the training phase. In the right panel, the robotic manipulandum Wristbot used by the subjects to control the pendulum.

2.3 Protocol

Three different phases were comprised in the protocol, for both groups: i. baseline (1 trial), ii. training (5 trials) and iii. test (3 trials). For the whole duration of each trial (2.5 minutes), participants were required to keep in balance the inverted pendulum for as long as possible, by controlling it acting on the angular orientation of the Wristbot handle. In between trials, they had 2.5 minutes of resting time to prevent fatigue from affecting performance. An additional real-time auditory feedback was provided whose magnitude increased with the angular distance between the pendulum and the vertical (i.e., the equilibrium). At the beginning of the experiment, it was explicitly explained to the subjects that during the training phase there would have been physical assistance facilitating the task coming from the Wristbot or iCub, depending on the experimental condition. For the *iCub group*, the humanoid robot iCub also showed some social behaviors, which however did not adapt to participants' performance, to emulate the condition in the Control group where no feedback was provided by the Wristbot. Before starting the baseline, iCub introduced itself and gave a brief introductory explanation about the task objective. At the beginning of the training trials, it looked at the participant's face and prepared itself to play, then it invited participants to get ready by saying an exhortation, such as "Let's start". When the game started, iCub followed the pendulum with its gaze and performed specific prono-supination movements of its forearm to mimic the control on the pendulum. At the end of the session, it invited the subject to take some minutes of rest before starting the next trial. It pretended to take a rest as well, looking around in the room in an exploratory way. During baseline and test sessions, iCub remained in its rest position and looked at the subjects performing the task, by alternating its gaze fixation point between the tool and the subject's face. The robot exhibited a happy, friendly face for the whole duration of the experiment, except during the training phase in which it looked at the pendulum with a focused expression. Except for the face-tracking behavior, the robot behavior was pre-programmed and not responsive to stimuli from participants.

Questionnaires Participants of both groups were required to compile questionnaires at the end of the experiment: the NASA-TLX workload assessment [6] and a short version of the Intrinsic Motivation Inventory (IMI) [1], comprising 14 items from the sub-scales Competence, Effort/Importance, and Interest/Enjoyment. Also, participants of iCub group were asked to fill in some questionnaires regarding their perception of the robot, among which the scales *Anthropomorphism*, *Animacy*, *Likeability*, and *Perceived Intelligence* of the Godspeed questionnaire [3]. See [4] for a more detailed description.

2.4 The Task

The task was designed to meet an optimal challenge level, without resulting too easy and leading to a lack of interest, or too arduous and preventing learning. To achieve this goal, we implemented a virtual dynamics that determined the angular orientation of the pendulum starting from the angular orientation of the Wristbot. The dynamics included a non-linear spring, which virtually connected the Wristbot to the pendulum, and an unstable viscous force-field in which the pendulum moved. An initial pilot study was conducted on a similar sample population to choose the parameters of the virtual dynamics, the average trial duration, and the number of trials needed to learn the successful strategy. During the training phase, participants experienced facilitated dynamics thanks to assistance that reduced the instability of the viscous force-field of 30%. The assistance level was selected after piloting, and it wanted to emulate the help of an expert trainer that intervenes in the task by dampening the fall of the pendulum, making it easier to control. The training phase was thought not to fully counterbalance the instability, but rather to facilitate the task while maintaining it still challenging. The assistance was constant during the whole training phase and did not adapt to participants' performance. This choice met the need to keep the two experimental conditions as comparable as possible. In the test phase participants had to accomplish the same task they faced in the baseline (with no assistance); we could then assess whether they could generalize the skill learned during the training.

2.5 Data Analysis

Kinematic Data Starting from the wrist position, i.e. the angular wrist displacement in the range ± 60 degrees, sampled at 100 Hz and low-pass filtered at

8 Hz, the angular velocities and accelerations were computed through a sixth-order Savitzky-Golay low-pass filter (10 Hz cut-off frequency). For each trial, different features in time and frequency domain were computed starting from the wrist velocity and acceleration signals (Time Domain: 1. Mean Amplitude (MEAN), 2. Maximum Amplitude (MAX), 3. Standard Deviation (SD), 4. Root Mean Square (RMS), 5. Maximum Amplitude Variation (PP), 6. Skewness (SK), 7. Kurtosis (KRT), 8. Crest Factor (CF), 9. Number of Peaks (PKS); Frequency Domain: 10. Maximum of the Power Spectrum Density (MAX_POW), 11. Dominant Frequency (DF), 12. Total Power (POW), 13. Power Ratio (PR)). After having tested windows of different lengths (1, 1/3, 1/5, and 1/10 of the whole trial duration) to determine the optimal one, we choose the one which gave us the best model accuracy, i.e. 1/3. Subjects' performances were computed as a weighted sum of the pendulum angular positions. In this way, participants who held positions around the vertical for longer were rewarded with higher scores. Therefore, the performances were continuous values expressed in percentage. Since we aimed to test whether it was possible to infer subjects' performances starting from the kinematic features of the wrist and to identify the more informative features able to discriminate between a successful and an unsuccessful strategy, we discretized subjects' performances and turned into a classification problem. Specifically, performances above a certain threshold (computed as the mean performance of the whole population and equal to ∼61%) were labeled as *good performance* and performances below that threshold were labeled as *bad performance*. Starting from the assumption that the successful strategy did not change among the two groups conditions, and in order to exploit as much data as possible, we trained a machine learning classification model with all the observations from the 32 subjects, excluding the trials of the five training sessions, in which the task was facilitated by the assistance. Considering that each trial was divided into 3 windows of the same length, our final dataset consisted then in 384 observations and was balanced, with a ratio between good and bad performance equal to 0.50. Features were rescaled trough Z-score normalization such that they had the properties of a standard normal distribution with a mean of zero and a standard deviation of one. We implemented a Logistic Regression model with the Elastic-Net regularization method. We followed a 10-fold cross-validation procedure with a nested 5-fold cross-validation for optimal hyperparameter tuning. To enforce sparsity we set *l1_ratio* hyperparameter equal to 0.95. We tuned the regularization parameter C using logarithmic spaced values in the interval $[10^{-2}; 10^{2}]$. The sparsity regularization approach allowed us to have an insight into the most informative features of the model, by acting on the coefficients of the correlated predictor and shrinking towards zero the less relevant ones. The model was implemented using Scikit-Learn library [11].

Affective Data To analyze subjects' facial expressions we used the *FaceChannel* neural network [2]. The *FaceChannel* is a lightweight convolutional neural network that allows for fast training and fine-tuning of facial expressions. It presents a compact architectural design with state-of-the-art facial expression

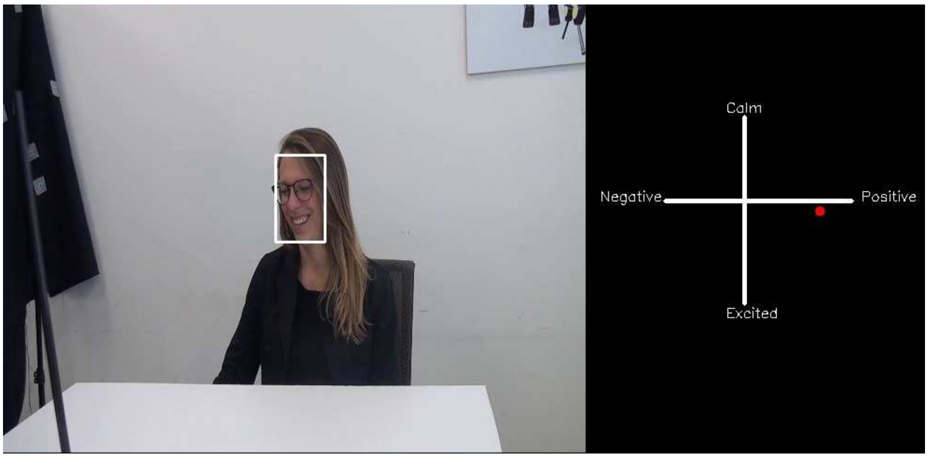

Fig. 2. Example of the *FaceChannel* network output, showing the Arousal and Valence values for each processed video frame.

recognition and which allows for fast inference times, endowing it with the capability to be deployed in the real-time analysis of the recorded videos. The *FaceChannel* was trained using a large-scale dataset with more than 1 million datapoints and it can describe a facial expression using a continuous representation of Arousal and Valence. We processed each video by localizing the face using the caffee-based face detector of OpenCV [4] in each of the video's frame. We then resized each detected face to a dimension of 96x96 pixels and fed it to the *FaceChannel*. The network outputs Arousal and Valence within the range of -1 and 1, representing calm/negative and excited/positive respectively for each face (Fig. 2). We considered in the analysis only the portions of videos in which the subjects performed the task (plus ∼3 seconds before and after the task execution) since in this phase we were mainly interested in studying the expressiveness of the naive subjects while learning the new motor skill, to potentially exploit in the future these implicit communicative signals and retrieve information about their status. The data were then smoothed with a median filter of 0.5 seconds. Due to technical failures, some video data were missing (2.08% for the *iCub group* and 5.56% for the *Control group*). Data were compared among different sessions or between different groups through ANOVAs. When data resulted not following the sphericity assumption, a Greenhouse-Geisser correction was applied. The data resulting from questionnaires were also analyzed to investigate whether some correlation exists between the perception of the robot iCub and the observed expressiveness. The details of each analysis are reported in the results.

[4] https://opencv.org/

3 Results

3.1 Classification Model

Since the strategy leading to a successful outcome was not known a priori, we tested whether it was possible to infer the skill level of the naive learners on the basis of some regularity of the wrist movement. The machine learning classification model trained with the wrist's velocity and acceleration features of all the subjects had a mean accuracy of 76.80±7.43%. The most recurrent best C was 3.16. In order to interpret the model's coefficients and assess the most relevant features, we trained the model fixing C to 3.16 and *l1_ratio* to 0.95. This model gave a test accuracy of 76.26±7.20%.

All the model coefficients are shown in Fig. 3. The higher the amplitude of coefficients, the higher was the contribution of the corresponding features to the model classification. Specifically, as you can see from the figure, the features that resulted most informative for the model were the standard deviation and the average value of the wrist velocity, together with the mean and the power of the spectrum of the acceleration. This can be interpreted indeed as the need for subjects of making rapid and frequent wrist movement adjustments to keep the pendulum in balance. The robot tutor can be provided with such knowledge and improve the assistance by acting (directly or indirectly) on the movement strategy adopted by the learners, by intervening specifically on their kinematic pattern.

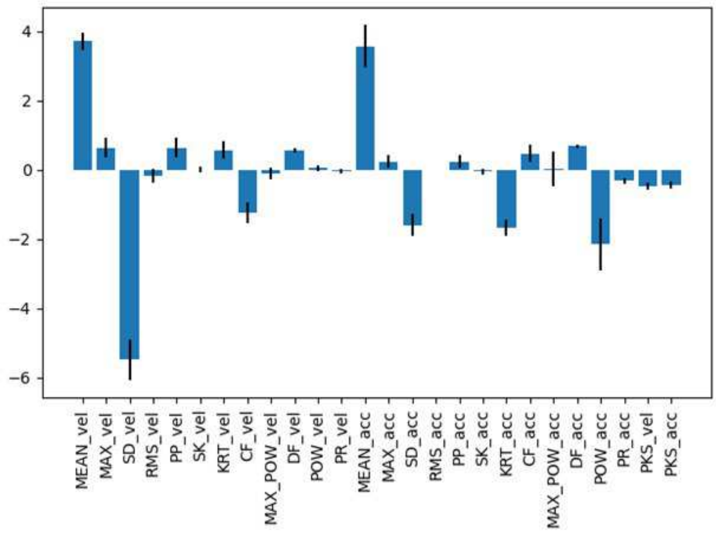

Fig. 3. Average coefficients of the classification model.

3.2 Communicative Behavior

To test whether subjects' expressiveness significantly changed among the different sessions (i.e., baseline, training, and test), and between the 2 groups, we performed a Mixed Model ANOVA with "sessions" as within factor and "groups" as between factor. For Valence, the results showed that there was a significant effect of sessions ($F(1.34, 28.1) = 8.54$, $p < .01$), while there was not significant effect of groups ($F(1, 21) = 0.724$, $p = .40$), nor of the interaction between the two ($F(1.34, 28.16) = 0.376$, $p = .67$). A post-hoc Tukey test revealed that the significant effect of sessions reflected a significant difference in Valence between baseline and training (p < .01) and between baseline and test (p < .01) (Fig. 4). These results indicated that while participants showed positive Valence when approaching the challenging task for the first time, in the following sessions they tended to be more neutral or even showed negative Valence. For Arousal, the ANOVA did not reveal any significant effect of group (F(1, 21) = 2.39, $p = .14$) or session ($F(2, 42) = 1.44$, $p = .25$). Only the interaction approached significance ($F(2,42) = 3.05$, $p = 0.058$), with a tendency for Arousal to decrease over trials towards negative values in the *Control group.* These results suggested that over the duration of the experiment participants modified their facial expression and it was possible to detect a significant modification in their Valence.

On average the pattern of such changes was very similar between the two groups, i.e., with and without the social humanoid tutor. It seemed therefore more driven by the task than by the presence of a partner. We should consider, however, that the task designed led subjects to stay constantly focused on the pendulum position, so their expressiveness when performing the task was limited. Moreover, we did not found any significant interaction between performance and facial expression, meaning that poor outcomes in task performance are not necessarily reflected in negative emotions and vice versa. At the same time, positive emotions are not necessarily predictive of successful performance. This suggested that the relations between users' state and performance are not trivial and above all, they cannot be generalized under predefined rules.

To test whether subjects' expressiveness was communicative of their self-reported states, we performed Pearson correlation between affective data and the scores of the post-questionnaires (namely IMI and NASA-TLX). The results showed that the mean Valence correlates significantly (and positively) with the Frustration score of NASA-TLX questionnaire ($r(13) = 0.53$, $p = .043$), but only for the *iCub group.* However, when performing Spearman correlation this tendency is no more significant ($r_s(13) = 0.44$, $p = .09$).

No significant correlations were found instead for the *Control group* between facial expressions and self-reported measures. Lastly, to further explore potential relations between the evaluation of the robot iCub and expressiveness, we performed correlation between post-questionnaires sub-scales regarding robot perception and Arousal and Valence values. A significant negative correlation between Valence and *Anthropomorphism* subscale of *Godspeed* questionnaire was found (*Pearson's* $r(14) = -0.54$, $p = .032$; *Spearman's* $rho(14) = -0.61$, $p = .012$),

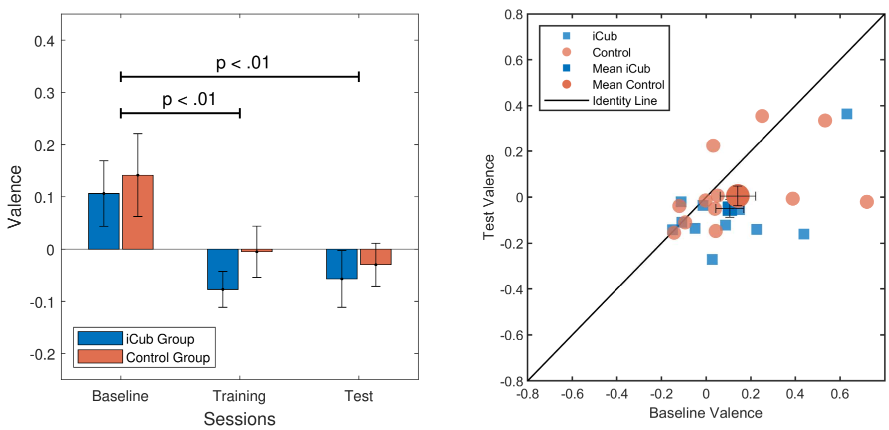

Fig. 4. Mean and Standard Error of Valence for each group in the different sessions (left panel). Valence in baseline versus Valence in test for each subject of the two groups (right panel).

meaning that participants who ascribed higher anthropomorphic traits to iCub showed lower values of Valence.

4 Discussion

In this study, we started to address the issue of the need to integrate different communication signals in the assistive architecture of robot tutors. Indeed, we state that for motor learning to be effective and to optimize the experience of naive humans, robots should integrate into their decision-making process physical and performance-related information with social and affective cues. To this aim, we proposed a novel experimental design where it is possible to record and send both haptic signals, by using the robotic handle Wristbot, and social cues, through the humanoid robot iCub. We asked participants to learn a complex task, namely to balance an unstable inverted pendulum, in two different experimental conditions: one that involved training with the humanoid robot iCub, embodying the physical assistance, and one in which participants had to perform the same training but using the Wristbot alone. In a previous study [4], we have demonstrated that both groups effectively acquired the skill by leveraging the physical assistance as they significantly improved their stabilization performance even when the assistance was removed; moreover, learning in a context of interaction with a humanoid robot assistant led subjects to increased motivation and more enjoyable training experience, without negative effects on attention and perceived effort. In this study, we wanted to take a step further and investigate deeply the relative contribution of the different communicative channels to understand which information the robot tutor should exploit in the future to enrich its knowledge about user's skills and emotional state, to build a comprehensive and exhaustive user model to rely on when assisting. To answer our research questions, we computed and analyzed several kinematic features of the wrist movement and implemented a machine learning classification model to infer the performance of subjects of both groups. A Logistic Regression model with Elastic-Net regularization was able to predict the performance of the subjects with an accuracy of 76.26±7.20%. The sparsity method allowed us to rank the most informative features of the model. These results allowed us to acquire a more solid knowledge of the strategy needed to succeed in the task, not known a priori. The results indicated that the variation and the mean of the wrist velocity are the most relevant features for an effective balancing strategy. This means that the social robot tutor could improve the assistance by directing the attention of the learners on these parameters, suggesting them to keep the wrist velocity high and stable, or, if necessary, delivering directly physical assistance. Then we wanted to test whether and how the affective state of the participants, described in terms of Arousal and Valence computed from their facial expressions, changed among sessions and group conditions. The Valence recorded in the baseline was significantly higher than the one detected by the software in the training and test sessions. We believe that the novelty component and the difficulty experienced in the first trial provoked the higher expressivity of the naive participants. No significant difference was found in the amount of Arousal and Valence between the 2 groups, probably because the task required high and continuous focus on the pendulum, limiting the variability of expressiveness. Of interest, when testing whether the expressive behavior of the subjects correlates with the self-reported measures of the post-questionnaires, we found a significant relationship between frustration score and Valence values only in the *iCub group*, while no significant correlations were found for the *Control group*. These results lead us to speculate that the presence of the embodied agent seemed to influence the communicative intent of their expressiveness as if to make their emotional states explicit and easily readable by the partner. The outcomes of the correlation between iCub perception and affective state showed that subjects who ascribed higher anthropomorphic traits to iCub presented lower values of Valence when involved in a complex and challenging task. As future development of this work, we are interested in reading both motor behavior and affective states in real-time to build an adaptive assistive architecture, which will allow us to get closer to robots that are not just assistive devices but rather assistive partners, able to guide humans in both short-term and long-term processes of skills learning and recovery and to adapt to their needs through a customized interaction.

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References

1. Adams, N., Little, T.D., Ryan, R.M.: Self-determination theory. In: Development of self-determination through the life-course, pp. 47–54. Springer (2017)
2. Barros, P., Churamani, N., Sciutti, A.: The facechannel: A light-weight deep neural network for facial expression recognition. In: 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020)(FG). pp. 449–453
3. Bartneck, C., Kulić, D., Croft, E., Zoghbi, S.: Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. International journal of social robotics **1**(1), 71–81 (2009)
4. Belgiovine, G., Rea, F., Zenzeri, J., Sciutti, A.: A humanoid social agent embodying physical assistance enhances motor training experience. In: 2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN). p. to appear. IEEE (2020)
5. Fasola, J., Matarić, M.J.: Robot motivator: Increasing user enjoyment and performance on a physical/cognitive task. In: 2010 IEEE 9th International Conference on Development and Learning. pp. 274–279. IEEE (2010)
6. Galante, F., Bracco, F., Chiorri, C., Pariota, L., Biggero, L., Bifulco, G.N.: Validity of mental workload measures in a driving simulation environment. Journal of Advanced Transportation **2018** (2018)
7. Galofaro, E., Morasso, P., Zenzeri, J.: Improving motor skill transfer during dyadic robot training through the modulation of the expert role. In: 2017 International Conference on Rehabilitation Robotics (ICORR). pp. 78–83. IEEE (2017)
8. Iandolo, R., Marini, F., Semprini, M., Laffranchi, M., Mugnosso, M., Cherif, A., De Michieli, L., Chiappalone, M., Zenzeri, J.: Perspectives and challenges in robotic neurorehabilitation. Applied Sciences **9**(15), 3183 (2019)
9. Masia, L., Casadio, M., Sandini, G., Morasso, P.: Eye-hand coordination during dynamic visuomotor rotations. PloS one **4**(9), e7004 (2009)
10. Metta, G., Natale, L., Nori, F., Sandini, G., Vernon, D., Fadiga, L., Von Hofsten, C., Rosander, K., Lopes, M., Santos-Victor, J., et al.: The icub humanoid robot: An open-systems platform for research in cognitive development. Neural networks **23**(8-9), 1125–1134 (2010)
11. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al.: Scikit-learn: Machine learning in python. the Journal of machine Learning research **12**, 2825–2830 (2011)
12. Spaulding, S., Gordon, G., Breazeal, C.: Affect-aware student models for robot tutors. In: Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems. pp. 864–872 (2016)
13. Vasalya, A., Ganesh, G., Kheddar, A.: More than just co-workers: Presence of humanoid robot co-worker influences human performance. Plos one **13**(11), e0206698 (2018)
14. Zenzeri, J., De Santis, D., Morasso, P.: Strategy switching in the stabilization of unstable dynamics. PloS one **9**(6), e99087 (2014)