Neural correlates of motor learning and performance in a virtual ball putting task

1Lorenzo Pitto, 1,2Vladimir Novakovic, 1,2Angelo Basteris, 1,2Vittorio Sanguineti
1Department of Informatics, Systems and Telematics
University of Genoa
Genoa, Italy
vladimir.novakovic@unige.it
2Department of Robotics, Brain and Cognitive Sciences
Italian Institute of Technology
Genoa, Italy

Abstract — Learning to move skillfully requires that the motor system adjusts motor commands based on ongoing performance, until the task is executed satisfactorily. Robots can be used to emulate motor tasks that involve haptic interaction with objects. These studies may provide useful insights on how humans acquire a novel motor skill. Here we address motor skill learning in a 2D ball putting task, by looking at both kinematic and EEG correlates of learning and performance. Participants grasped the handle of a manipulandum and had to hit a virtual ball in order to put it into a target region (hole). The robot was used to render the contact force with the ball during impact. At every trial, with respect to the initial ball position, the hole appeared in one of three different directions and two distances, selected randomly. The experimental protocol included a total of 300 movements. In movement kinematics we looked at the effects of learning and target distance. In EEG signals, we looked at the effect of learning and the effect of success/failure on the ongoing brain activity. Subjects managed to improve their performance through practice, in all directions and at both target distances. Direction did not affect the performance much, but greater target distance induced greater errors. With regards to the EEG activity, we found that (i) practice led to an increased theta synchronization in the frontal areas; (ii) successful trials were preceded by higher theta synchronization, and alpha and beta desynchronization. These results suggest that EEG signals can be used to monitor the learning process and to predict the outcome (success/failure) of individual trials. These findings open possibilities to develop new schemes to promote and facilitate learning, which integrate EEG and robots.

I. INTRODUCTION

Because of their ability to simulate a variety of dynamic environments, robotic devices have opened a new chapter in human motor control studies [1]. Robots have been used to study sensorimotor adaptation, and to provide assistive forces in order to promote neuromotor rehabilitation. In addition, robots could be used to implement motor tasks that involve haptic interaction with objects. These studies may provide useful insights on how humans acquire a novel motor skill. A better understanding of these mechanisms may turn out to be crucial to derive novel approaches to neuromotor rehabilitation [2].

Neural correlates of movement are another important source of information about the motor skill learning processes [3]. However, this requires a precise characterization of the neural correlates of different aspects of performance. In particular, the ways EEG activity before or during movement reflects task difficulty and the progress of the learning process have to be identified.

EEG studies in humans have revealed movement-related brain activity in the sensorimotor and frontal areas during movement preparation, movement execution and motor imagery. Theta band (usually defined as 4-8Hz band) is mainly localized in the frontal midline regions of the scalp and is thought to be generated by the prefrontal cortex [4], [5]. It was directly associated with the augmented cognitive demands. More particularly, memory demands [6], [7], attention [8], as well as visuomotor tasks [9] were found to induce event-related increase in theta band power, i.e. event-related synchronization (ERS). Alpha rhythm (usually between 8Hz and 12Hz) was generally thought of as an idling rhythm, but new studies have shown that this notion is no more tenable and proposed that alpha rhythm more likely reflects active inhibition of task-irrelevant processes [10]. Moreover, it was suggested that alpha desynchronization can be related to the cortical activation of the particular area [11]. Such desynchronization can be seen in the motor preparation and execution as well as in motor imagery [11], [12], [13]. Beta band activity (localized between 13Hz and 30Hz) was also found to be fairly modulated due to movement execution/imagery. It was reported that beta band ERD precedes the arm movements, which is immediately followed by a post-movement beta ERS [14].

In this study, we use robots and EEG recordings to look at motor learning and its neural correlates in a tool manipulation task, namely ‘virtual’ ball putting.

To better understand the neural mechanisms behind movement preparation/execution, we specifically looked at how performance and its changes are reflected in brain activity. In addition, we looked at neural correlates of task outcome (success/error). As the emphasis of this work is on neural correlates, we only provide a limited account of kinematic changes during learning.
II. METHODS

A. Experimental apparatus

The experimental set-up involved a planar robotic manipulandum with two degrees of freedom – Braccio di Ferro (see [15] for details). Subjects were seated on a chair, with their torso and wrist restrained by means of suitable holders while grasping the handle of the manipulandum with their dominant hand. A light support was connected to the forearm to provide low friction movements. In this way, movements were restricted to the horizontal plane, with no influence of gravity. Seat position was also adjusted so that, with the hand pointing at the centre of the workspace, the elbow joint was anteflexed about 90° and the shoulder was horizontally abducted about 45°, while the arm was kept approximately horizontal, at shoulder level. A 19” LCD computer screen, positioned at eye level about 1 m away, was used to display the virtual environment. The scale factor of the display was 1:1, i.e. 1 cm in the monitor corresponded to 1 cm in the robot workspace.

EEG signals were recorded before and during each movement. Previous studies suggest that frontal and sensorimotor regions are most likely to reflect motor planning and execution, as well as cognitive processing. To monitor neural activity in these regions, we used 13 gold electrodes arranged on a electrode cap (g.EEGcap, g.tec, Graz, Austria) and placed at the following sites (International 10-20 electrode system): C5, C1, Cz, C2, C6, FC3, FCz, FC4, F5, F1, Fz, F2, F6. EEG signals were recorded with respect to linked ears reference, amplified (b.BSamp, g.tec, Graz, Austria) and stored for subsequent analysis. Amplifier ground was connected to the subjects’ nose. Special care was taken to properly ground the robot and to isolate its handle in order to minimize the effect of noise on the EEG signal.

This study involved a total of seven subjects (5M + 2F), with mean age 24±1 years. All subjects were right-handed. Subjects’ handedness was assessed with the Edinburgh test; mean score was 65±15. All subjects were naïve to the task and none of them had neither neurological nor neuromuscular disorders. The research conforms to the ethical standards laid down in the 1964 Declaration of Helsinki that protects research subjects. Each subject signed an informed consent that confirms these guidelines.

B. Task and experimental protocol

We focused on a 2D golf-like putting task. Subjects were required to hit a virtual ball with the handle of the manipulandum (the ‘pad’) in order to put it into a target region (the ‘hole’); see Fig. 1. The robot was used to render the contact force with the ball during impact. The current position of the pad was continuously displayed, as a red circle (2 cm diameter) on a black background. The ball and the target were also displayed, as a blue and yellow circles (diameters 2 cm and 3 cm), respectively. At each trial, the hole was placed in one of the three randomly selected directions (0°, 90° and 180°), at either 6 cm (near) or 12 cm (far) away from the start position.

The experiment was organized into 10 epochs, each consisting of 30 trials. Each epoch consisted of 5 repetitions of a random sequence of all 6 direction × target distance combinations. At the beginning of every trial, subjects had to move to a starting position, located at the bottom of the screen. A 3-s baseline period started as soon as the pad was in the start position a baseline/rest period started (top-2), immediately followed by a preparation period where a visual cue (target) was given (top-3). After the preparation time (of random duration 1.8s to 2.3s) the ball appeared (GO signal, top-4). For EEG analysis purposes, we took 3 time intervals of interest T1-T3 lasting 600ms, 350ms and 350ms, respectively, from T1 to T3; for the baseline we took a 1-s interval from -1100ms to -100ms. Note that the timeline was rescaled for symmetry purposes.

![Figure 1 Structure and timeline of one individual trial. The subjects had to move the red cursor to the start position (top-1). As soon as the pad was in the start position a baseline/rest period started (top-2), immediately followed by a preparation period where a visual cue (target) was given (top-3). After the preparation time (of random duration 1.8s to 2.3s) the ball appeared (GO signal, top-4). For EEG analysis purposes, we took 3 time intervals of interest T1-T3 lasting 600ms, 350ms and 350ms, respectively, from T1 to T3; for the baseline we took a 1-s interval from -1100ms to -100ms. Note that the timeline was rescaled for symmetry purposes.](image-url)
C. Data analysis

Kinematic data were recorded at a sampling frequency of 60Hz. These data were smoothed using a 4th order Savitzky-Golay filter, with a 270 ms time window (equivalent cut-off frequency: 7.5Hz). We used the same filter to estimate the velocity as the first derivative of the trajectory. For each trial, we computed hand (pad) impact velocity (velocity at the instant when the collision between ball and pad occurs), final ball position (position of the ball when it has stopped) and final error (distance between the center of the hole and the center of the ball once it stopped). Analysis of the kinematic data was conducted using MATLAB (Mathworks Inc.).

EEG signals were sampled at 256 Hz and stored for later analysis (no on-line processing was performed). Synchronization between robot and EEG recording system was achieved using a direct link between the two computers’ I/O cards. The robot PC generated a TTL synchronization signal, which was connected to one of the channels on the EEG computer I/O card.

Off-line processing of the EEG data was conducted using the EEGLAB package (sccn.ucsd.edu/eeeglab/), based on MATLAB. Signals were band-pass filtered between 0.5 and 40Hz to remove linear trends and electrical noise. The epochs in which the signals were extremely corrupted were discarded, hence completely removed from further analysis. Likewise, the trials that were performed incorrectly (anticipated and late starts) were also eliminated from analysis. Overall, we had 15%-5% of corrupted trials.

Once the corrupted epochs were removed, an independent component analysis (ICA) was run in order to identify and eliminate eye blinking and movement artifacts. Finally, the EEG signals were band-pass filtered to identify the contributions in the theta (4-8 Hz), alpha (8-12 Hz) and beta (low 13-18 Hz, high 18-30 Hz) bands. As in [16], we then estimated event-related synchronization (ERS) and desynchronization (ERD) as the percent change of the signal power spectral density $P_{\text{interval}}$, relative to that of the signal recorded during a reference period, $P_{\text{base}}$:

$$\text{ERD/ERS} = \frac{P_{\text{interval}} - P_{\text{base}}}{P_{\text{base}}} \times 100$$

Baseline power spectral density ($P_{\text{base}}$) was recorded from 1100 ms to 100 ms before visual cue onset (-1100ms < t < -100ms). We then calculated ERD/ERS for three time intervals: CUE < t < CUE+600ms (T1, Post-CUE), GO < t < GO+350ms (T2, Post-GO) and MOV-350ms < t < MOV (T3, before-MOV); where CUE and GO are defined above, while MOV was simply the instant when subjects started the movement (Fig. 1). Finally, we compared ERD/ERS in early vs. late and successful vs. unsuccessful trials for all 3 time intervals (T1-T3).

D. Statistical analysis

A three-way ANOVA was applied on kinematic data. More specifically, we tested the influence of Direction (0°, 90° and 180°), Target distance (near, far) and Phase (early, late) on the final error.

In the case of EEG data, we performed a three-way ANOVA on the ERD/ERS values for each band (theta, alpha, beta low and beta high) and each time interval (T1-T3). Factors of such ANOVA were EEG Channel, Target distance (near, far) and Phase (early, late). Additionally, another three-way ANOVA was used to test the effect of Channel, Target distance (near, far) and Error (successful and unsuccessful trials). Post-hoc analysis (Tukey’s Honest Significant Difference test) was used where appropriate.

III. RESULTS

A. Kinematics

As mentioned in the Methods, we focused on final ball position and on pad (hand) velocity just before impact. In the Fig. 2, we show dispersion ellipses for both (a) impact velocity and (b) final ball position, for a typical subject.

It can be seen that in the early phase the dispersion of velocity and final ball position is high, but it tends to decrease with practice, showing a steadier performance in the late phase of the experiment.

Learning of this task is reflected by the temporal evolution of the error in final ball position. Final error, averaged for near and far targets separately within each block of 6 trials across the three directions, is shown in Fig. 3.

There are two main effects that can be seen: (i) final error is higher for far targets and (ii) in both near and far targets, ANOVA confirmed that subjects improved their performance - we found a significant (F(1,83)=83.7, p<0.0001) effect of Phase on the final error. As regards task difficulty, statistical analysis also showed a significant Distance effect (F(1,83)=56.36, p<0.0003), thus confirming the observation that errors were greater for far targets. Finally, we found a significant (F(2,83)=4.23, p<0.05) Distance×Direction, suggesting that performance changed in the different directions.

In order to successfully putt the ball in the hole. Final ball position (b) reflects the task outcome (black circles represent holes). Dispersion ellipses shown are from early (red) and late (light-blue) phase of the experiment for a typical subject.
Overall, kinematic results indicate that it was more difficult to put the ball in the far holes. Nevertheless, subjects improved their performance with practice irrespective of target distance.

B. EEG signals

In EEG analysis, we specifically probed two different effects: (i) effects of learning and target distance, and (ii) effect of performance. Furthermore, both effects were analyzed for near and far targets separately, and for each of the frequency bands considered.

1) Effects of learning and target distance

Kinematics analysis clearly indicates that subjects improve their performance with practice. In order to find out if this change in performance was reflected or driven by changes in cortical activity, the first and last 30 trials for each target distance were selected and compared.

a) Theta band

EEG activity in the theta band expressed no significant modulation in the post-CUE (T1) and post-GO (T2) periods. However, in the before-MOV (T3) interval, we observed that theta-band ERS is greater in the frontal lobe and decreases with phase (Fig. 4).

Statistical analysis confirmed the significance of the Phase effect (F(1,72)=6.68, p<0.042) and a significant Channel×Phase interaction (F(12,72)=2.15, p<0.025). Post-hoc analysis showed that the Phase effect was significant over frontal and fronto-central electrodes (exception was the channel F5), but not in the central lobe.

b) Alpha band

EEG activity in alpha band exhibited no significant influences of target distance for neither of the time intervals T1-T3. However, in the before-MOV (T3) period the effect of Channel was significant (F(12,72)=2.32, p<0.015), due to desynchronization at the central contralateral lobe.

c) Beta band

In the low-beta band, statistical analysis revealed a significant effect of Distance (F(1,72)=6.19, p<0.05) in T3 interval (from ERS to ERD while going from ‘far’ to ‘near’ targets). Moreover, we found significant Channel×Distance interactions in T2 (F(12,72)=2.52, p<0.008), and in T3 (F(12,72)=2.32, p<0.015). In contrast, we found no consistent effect of learning/practice. On the other hand, in the high-beta band we found no significant effects for neither of the intervals.

In summary, we observed a decrease in theta ERS over the frontal lobe with practice (effect of learning), and a low-beta increase with target distance.

2) Effect of performance

To study the effect of performance, depending on the score we divided the trials in the late phase of the learning process into two groups: successful (final error ≤ 1.5 cm) and unsuccessful trials (final error > 1.5 cm). We then compared the differences between the two groups.

a) Theta band

Statistical analysis showed that in the theta band neither of the main effects reached significance level. However, Error×Channel interaction was found to be significant in post-CUE (T1) (F(12,72)=3.44, p<0.0005), and post-GO (T2) (F(12,72)=2.04, p<0.033) intervals.

Fig. 5a suggests that in the post-CUE (T1) interval, successful trials exhibited greater theta ERS over the central electrodes. Post-hoc analysis confirmed that ERS was
significantly greater in successful trials over central contralateral electrodes (C2 and C6) in T1, but not in T2. The effect of Error was not significant over frontal and fronto-central electrodes for neither of the two intervals (T1-T2).

b) Alpha band

Contrary to theta activity, a characteristic of successful trials in the alpha band was a high ERD over all areas in post-GO (T2) and before-MOV (T3) intervals. Statistical analysis confirmed that Error was significant in both T2 and T3 intervals, \( F(1,72)=10.28, \ p<0.019 \) and \( F(1,72)=22.89, \ p<0.003 \), respectively. Moreover, the effect of Channel was significant in T1 and T3. Finally, interactions Distance×Channel and Error×Distance×Channel were significant in T1-T3 and T2-T3 intervals, respectively.

Significance of the Channel effect is due to desynchronization in the central contralateral lobe (channel C5). On the other hand, the interactions are significant due to higher ERD in successful trials for the far targets in the contralateral hemisphere. However, post-hoc analysis showed no significant pairwise differences.

![Activity maps (topoplots) in the pre-movement phase for the successful (left) and unsuccessful (right) trials in the three bands: (a) theta ERD/ERS in the post-CUE (T1) interval (scale ±45%); (b) alpha ERD/ERS in the post-GO (T2) interval (scale ±25%) and (c) high-beta ERD/ERS in the post-CUE (T1) interval (scale ±20%).](image)

Figure 5. Activity maps (topoplots) in the pre-movement phase for the successful (left) and unsuccessful (right) trials in the three bands: (a) theta ERD/ERS in the post-CUE (T1) interval (scale ±45%); (b) alpha ERD/ERS in the post-GO (T2) interval (scale ±25%) and (c) high-beta ERD/ERS in the post-CUE (T1) interval (scale ±20%).

c) Beta band

In the low-beta band we observed significant differences only in post-CUE (T1) interval. More particularly, we found significant interactions Error×Channel (\( F(12,72)=1.89, \ p<0.05 \)) and Distance×Channel (\( F(12,72)=2.19, \ p<0.021 \)). Further pairwise comparisons revealed no significant effects of performance.

On the contrary, high-beta band exhibited an event-related desynchronization over all the electrodes regardless target distance and performance in the post-CUE (T1) interval. However, Fig. 5c suggests that successful trials induced higher ERD.

ANOVA confirmed the significance of the factor Error in T1 (\( F(1,72)=27.44, \ p<0.002 \)). Nonetheless, interaction Distance×Channel was significant in T1 (\( F(12,72)=2.28, \ p<0.02 \)).

In summary, we observed that in the theta band successful trials induce higher ERS in the frontal lobe, while in the alpha and beta bands success can be associated to higher ERD, especially in the contralateral hemisphere (effect of performance).

IV. DISCUSSION

A. Movement kinematics

A successful hit is determined by the velocity of the ball immediately after impact, which in turn depends on the pad velocity and active force just before impact. The correct determination of these movement parameters requires that subjects develop an ability of predicting the arm and robot inertia in different directions. In other words, the task requires a fine-tuning of an internal model of body dynamics.

Kinematic analysis revealed that subjects improved their performance through practice, in both near and far targets. However, the latter were much more demanding, even in the late phase of the experiment. Even though putting the ball in near and far targets was of different difficulty, in both cases we observed a gradual performance improvement. More specifically, the final error decreased significantly in either of the conditions (see Fig. 3). This suggests that for both target distances subjects were able to learn the arm inertia and adjust the impact velocity accordingly (see Fig. 2).

B. Frontal theta synchronization before movement reflects learning

One of the main findings of this study was that theta ERS before movement (T2 and T3) was higher in early trials and decreased with practice. As mentioned in Introduction, a number of studies reported a correlation between theta band activity and cognitive processes like attention, memory load and task difficulty. Our findings are consistent with those previous results, i.e. in the early phases we observed higher theta ERS corresponding to higher cognitive and attentional demands.

Furthermore, with practice theta ERS decreased as the task became easier and more automatic, which allowed subjects to reduce the amount of attention dedicated to it. According to this interpretation, a similar decrease was expected in the post-cue (T1) interval, but none was observed. This may be due to the fact that the CUE period was of variable length, thus
subjects started their planning closer to the more reliable GO signal. Alternatively, [17] and [18] report that only highly skilled subjects (e.g. elite athletes) exhibit distinct theta activity throughout the whole trial with respect to novices and with respect to early trials. Hence, the lack of the Phase effect in T1 is due to the fact that only naive subjects were involved in the experiment.

C. EEG activity before movement predicts subsequent performance

Different outcomes (success/error) of individual trials were reflected in considerable differences in cortical activation. Successful trials were preceded by a greater alpha ERD just before the movement. Moreover, just after the CUE signal successful trials exhibited a greater high-beta ERD and a greater theta ERS (in the central ipsilateral area).

Desynchronization is believed to denote cortical activation of the certain area in a certain band. Following this interpretation, alpha and beta band ERD before successful trials may indicate higher cortical activity. This result is consistent with [19], who reported higher alpha ERD before successful trials in a golf putt task. In a related study [20], in golf putt trials by experienced players, successful trials were preceded by an increased alpha power in the right hemisphere. We observed a similar effect in the theta band, where higher theta ERS predicted successful trials. With regard to the observed learning effect, this particular trend can be brought in correlation with higher cognitive processing (higher ERS) preceding successful trials. The differences we noted are most probably due to different tasks, i.e. real golf putt is a very complex movement involving many muscle groups and our experiment is just its slightly simplified 2-D projection. Therefore, it was expected to see different activity and more variability (less distinct correlates) than in our experiment.

V. CONCLUSIONS

Our findings clearly indicate that ball putting is a very challenging task, and reaching satisfactory performance takes a long time. Moreover, target (hole) distance plays an important role and can be used as gauge to increase or decrease the difficulty of the task.

For this task, we were able to identify correlates of performance and learning. In exercise protocols, an EEG-based BCI could be used to control a robot in order to supplement insufficient muscle control [3]. However, at least in principle, EEG brain signals could also be used to monitor the current state of patients’ brain activity during exercise, as biofeedback to enable patients to modify their abnormal activity, or to modulate the amount of assistance provided by a robot. A prerequisite is that neural signatures of mental fatigue and recovery and/or learning must be identified. In this experiment, we found neural signatures for the perceived task difficulty, performance and the progress of adaptation. In conclusion, the present study is a first step toward extending EEG-based brain-computer interfaces (BCI) from assistive to therapeutic applications [21].

ACKNOWLEDGMENT

The research leading to these results has received funding from the European Community’s Seventh Framework Programme (FP7/2007-2013) under grant agreement no FP7-ICT-231724 (HUMOUR)

REFERENCES