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Detection of movements with attention or distraction to the motor task during robot-assisted passive movements of the upper limb

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Abstract— **Robot-assisted rehabilitation therapies usually focus on physical aspects rather than on cognitive factors. However, cognitive aspects such as attention, motivation, and engagement play a critical role in motor learning and thus influence the long-term success of rehabilitation programs. This paper studies motor-related EEG activity during the execution of robot-assisted passive movements of the upper limb, while participants either: i) focused attention exclusively on the task; or ii) simultaneously performed another task. Six healthy subjects participated in the study and results showed lower desynchronization during passive movements with another task simultaneously being carried out (compared to passive movements with exclusive attention on the task). In addition, it was proved the feasibility to distinguish between the two conditions.**

I. INTRODUCTION

Neurological disorders or brain lesions such as stroke, cerebral palsy, or spinal cord injury may cause partial or complete loss of mobility in limbs. For people suffering any of the aforementioned motor disabilities, the rehabilitation programs, either assisted by a therapist or by a robotic device, aim to recover functionality in the impaired limbs [1]. Rehabilitation programs are based on the intensive and repetitive execution of therapeutic movements of the affected limbs, and aim at regaining and improving muscle strength, motor coordination, and dexterity [2]. Robot-assisted rehabilitation therapies are advantageous because they use information from force and kinematic sensors, or information from the peripheral nervous system (PNS) such as muscle activity (EMG), to drive and control movement-assisted devices. It has been demonstrated that rehabilitation programs may help maintain and promote neural cortical circuits that induce motor re-learning [3].

However, highly repetitive and non-challenging movements focus only on the physical aspects of rehabilitation, although cognitive factors (such as attention, motivation, and engagement) play an essential role in the outcome and success of therapy [4]. This occurs because the execution of movements during long time periods can diminish motivation and engagement, and can divert attention towards other mental tasks, thus, compromising the success of both the physical improvement and motor re-learning. Therefore the use of cognitive information such as attention to movements is essential to maintain rehabilitation strategy; this information can be directly measured from the central nervous system (CNS). For instance, if a reduction or loss of attention to movements is detected, this information could be used to enhance or change the motor task, reestablishing the patient's involvement in the therapy.

Although previous works have demonstrated that attention to sensory stimuli (visual, auditory, and tactile) modulates oscillatory EEG activity in the delta and gamma bands [5], [6], little is known on how attention to movements modulates brain activity and how to decode and apply this information to improve robot-assisted rehabilitation programs. Only a few fMRI studies demonstrated that reducing attention to movements is associated with a reduction in the activation of the sensorimotor cortical areas [7]. In addition, EEG studies have demonstrated the induction of event-related de/synchronization (ERD/ERS) during passive movements [8], [9], but the influence of attention on the movements in the ERD/ERS activation has not yet been studied.

The question is how attention to passive movements modulates oscillatory EEG activity, and how to distinguish when the patients are attending to or distracted from the motor task. The present work studies the influence of attention to movements in the sensorimotor brain oscillations during robot-assisted passive movements of the upper limb. A proposal is presented to recognize between passive movements with exclusive attention on the motor task or passive movements with attention focused towards another task. Six healthy subjects participated in this study and the results showed that different modulation levels in the sensorimotor EEG activity are induced and that it is feasible to recognize the two conditions.

II. METHODS AND MATERIALS

A. Data recording and Robot

1) EEG system: EEG activity was recorded by a gTec system (2 synchronized gUSBamp amplifiers), with 32 electrodes according to the 10/10 international system, with the ground on FPz and reference placed on the left earlobe. The EEG signals were acquired with a sampling frequency of 256 Hz, power-line notch-filtered and bandpass-filtered from 0.5 Hz to 100 Hz using a zero-phase shift filter.

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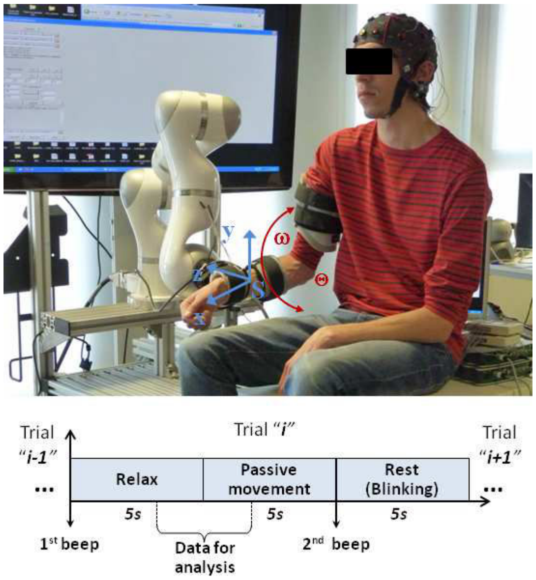


Fig. 1. Upper panel: Snapshot of the experimental setup showing a participant with the EEG and the robot attached to his right arm. Lower panel: Temporal sequence of one trial during the execution of the experiment.

2) Robot system: A 7 DoF robotic arm attached to the right arm was used for the experiment. The robot was programmed to perform natural and safe flexion-extension movements of the elbow, simulating the action of a therapist. The patient fixed the upper arm to a fixed structure and the forearm to the terminal element of the robot. The robot was equipped with an electric switch that sent a synchronization signal to the EEG system to record the actual onset and end of movements.

B. Experimental design

Six right-handed male healthy volunteers participated in the experiments (age range: $25-39$ years) after the protocol was approved by the Institutional Review Board of the University of Zaragoza.

The volunteers were seated in front of a computer screen with the right arm comfortably fixed to a rigid base and the robot‘s end-effector holding the middle part of the right forearm (Figure 1). The subjects were instructed to look at the screen and to relax while the robot executed flexion-extension movements through rotation of the elbow (only the forearm could be moved). The initial position of the right arm was fully extended and pointing down towards the floor. The final position was the maximum possible flexion that the subject could perform naturally and effortlessly. The left upper limb was resting on the subject’s lap.

The experiment consisted of two conditions. In both conditions the robot was programmed to execute the movements and the subjects were instructed to make no muscle contraction effort (passive movements or PM). For condition one, subjects were encouraged to focus their attention on the movement (passive movements with attention or *PM+A*). In condition two, the subjects had to mentally count back in threes, starting in a self-selected random three digit number for each trial (passive movements with distraction or *PM+D*). The system indicated the different phases of the experiment through two auditory cues (Figure 1) to the user. The first cue was given five seconds before robot motion. The user had to relax his body. After this period, the robot performed the total flexion-extension movement for five seconds. Then, the second cue marked the five seconds rest period before the next trial.

During the relaxing and movement periods, subjects were encouraged to maintain a natural and constant posture and to minimize blinking while maintaining the gaze fixed at the center of the screen (they had no visual access to the arm). For the remaining time, subjects were allowed to blink and rest. The experiment was executed in blocks of 7.5 min each (30 trials were recorded per block, each trial lasting 15 s), and 90 trials were recorded for each condition. Subjects rested between blocks.

C. Data Preprocessing

After the recording sessions, EEG signals were collected from -3 to 3 seconds with respect to the robot‘s movement onset (Figure 1). All EEG epochs were visually inspected and noisy (contaminated with EMG or EOG activity) trials were discarded and not used in further analysis. In each condition, the across-trials average was removed from the individual trials, to eliminate the evoked activity generated by the auditory stimulus presented during the experimental protocol.

D. ERD/ERS analysis

The power spectra at different frequency bands of the EEG activity was computed with a time-frequency analysis based on the complex Morlet‘s wavelet [10]. The time-frequency representation (TFR) was computed for all trials in each condition from 2 to 100 Hz with a frequency resolution of 1 Hz. The statistical significance of the power decrease (ERD) or increase (ERS) relative to the baseline in the time interval from -3 to 0 seconds was computed with the t-percentile bootstrap algorithm [11] with a significance level of α=0.01. This analysis was performed individually for each subject in each condition to obtain the statistical maps of ERD/ERS. ERD/ERS was compared in both conditions (*PM+A* and *PM+D*) to analyze the influence of attention to the movements in the sensorimotor brain oscillations.

E. Recognition of PM+A and PM+D

During robot-assisted passive movements it is important to detect whether the participant is attending to or distracted from the motor task. Therefore, a classifier was built to distinguish between *PM+A* and *PM+D*. For each trial, the spectral power of channels (located on the contralateral motor cortex) and frequency bins (in the motor-related bands) that presented significant desynchronization were computed using a 16th order autoregressive model [12] during the robot motion ($t \in [0, 3]$). The spectral power was used as features and fed to the classifier. Features were z-score normalized. A Support Vector Machine (SVM) with a radial basis function kernel was employed as it has been extensively used in different BCI applications [13]. The classification performance was assessed by a ten-fold cross validation procedure, where the full set of trials were sampled without replacement to create independent training and test sets for each fold. To measure performance: (i) classification accuracy was defined as the percentage of correctly classified labels, and (ii) the confusion matrix was computed in each fold and averaged for all of them.

III. RESULTS

A. ERD/ERS maps

Figure 2 shows for all subjects and for both conditions the ERD/ERS maps in one electrode located above the contralateral motor cortex (for each subject the electrode with the higher observed significant desynchronization was chosen). Note that although the ERD/ERS maps were calculated for the 2-100 Hz frequency range, no significant power increase or decrease was found in the γ band (>40 Hz). Therefore, only frequencies up to 50 Hz are shown. For all subjects (except subject 4), and in both conditions, the maps clearly show significant desynchronization in the α and/or β bands from 0 to 3 s. This desynchronization agrees with other studies reporting that motor-related brain oscillations are observed during passive movements [9], which is induced by the afferent input from the peripherals to the cortical areas activated in the execution of the motor task [8].

Note also that for subjects 1, 2, 3 and 6, the observed desynchronization is lower (or even absent) in condition *PM+D*. In order to examine these differences, the average of significant desynchronization contained in the α and β bands from 0 to 3 s were obtained in both conditions and for all subjects (the bounds for the bands were individually selected for each subject by visual inspection). These results are shown in Figure 3. For the α band, the results show that (except for subject 5) the desynchronization is greater in *PM+A* than in *PM+D*, and the average for all subjects is -41% for *PM+A* and -29% for *PM+D*. For the β band, the desynchronization is also greater in *PM+A* than in *PM+D* (although for subject 2 the differences were minimal), and the average for all subjects is -38% for *PM+A* and -27% for *PM+D*. In both bands, there is no desynchronization in subject 4, as shown in figure 2. These results suggest that the desynchronization in the motor cortex, induced during the execution of passive movements, is reduced when the subjects simultaneously performed another distracting task.

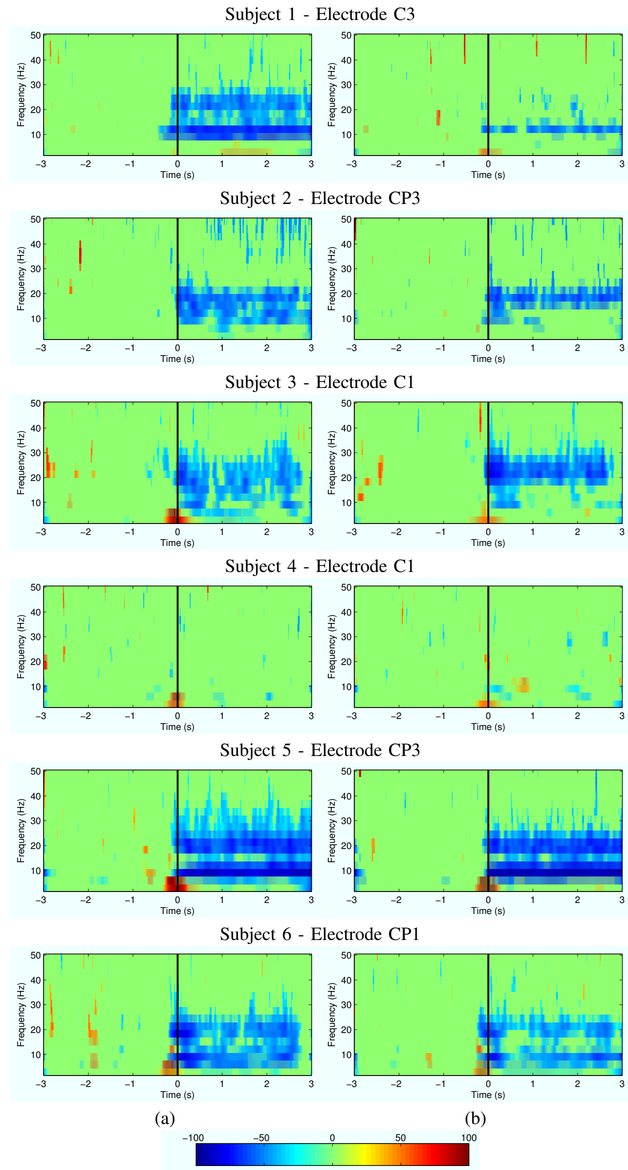


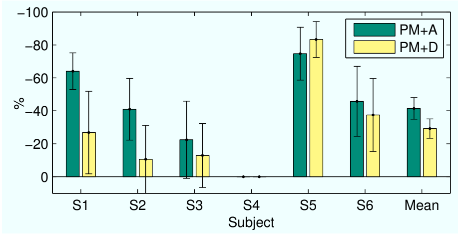
Fig. 2. ERD/ERS maps for all the subjects in the electrode with the higher observed desynchronization located above the contralateral motor area. (a) ERD/ERS maps for condition *PM+A*. (b) ERD/ERS maps for condition *PM+D*.

B. Classification results

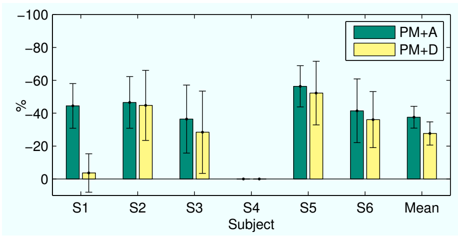
The classification accuracy obtained for all subjects and the overall average is shown in figure 4a. In the average for all participants, a significant ($p < 0.01$) classification accuracy of 76.37% was obtained (following [14] the chance level is 62.50%), which indicates a high performance in the recognition of *PM+A* and *PM+D*. Note that for subject 4 the classification accuracy (55.75%) is at the chance level, which is due to the spectral power features were not well discriminated between the classes (as no significant desynchronization was obtained). In addition, figure 4b shows the confusion matrix of the classification results averaged across subjects. This shows a slightly better performance in the recognition of *PM+A*. These results show the feasibility to detect whether, during robot-assisted passive movements, the attention is focused on the motor task or on another different task.

IV. CONCLUSIONS

This paper studied sensorimotor brain oscillations during the execution of robot-assisted passive movements of the right upper limb, while the participants focused their attention on the task or while they simultaneously performed another task. On one hand, significant desynchronization

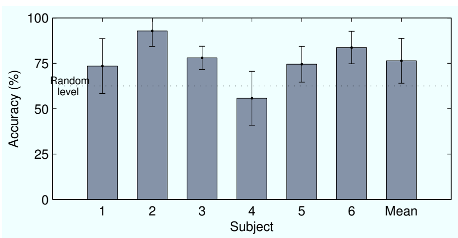


(a)

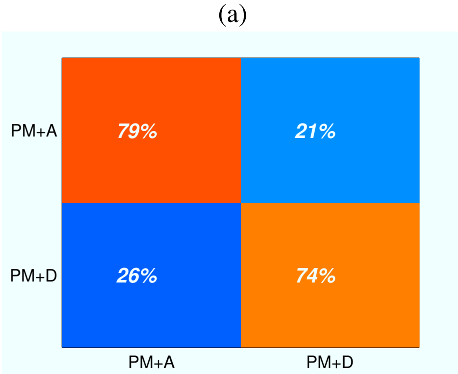


(b)

Fig. 3. Mean±std values of desynchronization contained in the (a) α and (b) β bands from 0 to 3 s for all subjects and the overall average.



(a)



(b)

Fig. 4. (a) Classification accuracy obtained for all subjects and the overall average. (b) Confusion matrix averaged for all subjects, for the classification of *PM+A* versus *PM+D*. Abscissa: real classes. Ordinate: predicted classes.

patterns in the motor-related frequency bands were obtained in electrodes located above the contralateral motor cortex. The induction of these motor rhythms is due to the processing in the motor cortical areas of motor information from the peripherals received through the afferent pathways [8], [9]. These patterns of desynchronization were less relevant when the subjects were asked to perform an additional task simultaneously. This suggests a reduction in the power of the motor rhythms during therapies based on intensive and repetitive execution of passive movements (as patients can easily be distracted towards another mental task), and therefore reducing the potential benefits of the therapy. On the other hand, this study examined the classification between passive movements with the subjects exclusively attending the task and passive movements with the subjects simultaneously performing another task (*PM+A* versus *PM+D*). The high accuracy of classification results indicated the feasibility to discriminate between them. These results are potentially interesting for applications in movement-assisted devices, as this information could be used to indicate to the system that the therapy is not being fruitful and thereby to enhance or to change the therapeutic paradigm. Finally, the authors understand that the application towards patients with real motor impairments (such as those produced by spinal cord injuries) requires further investigation, as the lesions could affect the afferent pathways that interconnects the limbs with the cortex, and thereby eliminating the induction of the motor rhythms.

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