PRE-MOVEMENT CONTRALATERAL EEG LOW BETA POWER IS MODULATED WITH MOTOR ADAPTATION LEARNING

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ABSTRACT

Various neuroimaging studies aim to understand the complex nature of human motor behavior. There exists a variety of experimental approaches to study neurophysiological correlates of performance during different motor tasks. As distinct from studies based on visuomotor learning, we investigate changes in electroencephalographic (EEG) activity during an actual physical motor adaptation learning experiment. Based on statistical analysis of EEG signals collected during a force-field adaptation task performed with the dominant hand, we observe a modulation of pre-movement upper alpha (10–12 Hz) and lower beta (13–16 Hz) powers over the contralateral region. This modulation is observed to be stronger in lower beta range and, through a regression analysis, is shown to be related with motor adaptation performance on a subject-specific level.

Index Terms— EEG; motor learning; force-field adaptation; pre-movement; brain-computer interfaces

1. INTRODUCTION

Stroke is a common cause for restricted activities of daily living for millions of patients. People severely affected by stroke are often left in a locked-in state with sustained loss of voluntary muscle control. In order to provide valuable insights into the understanding of stroke and the neural processes in the brain related to the complex nature of human motor behavior, post-stroke recovery is often studied as a form of motor learning in several neuroimaging studies [1]. To date, various experimental approaches have been proposed to identify neurophysiological correlates of motor learning.

Several pieces of previous work have studied the concept of visuomotor learning using simultaneously recorded EEG data. Independently of the neural activity during motor execution, EEG correlates of visuomotor task performance during pre-movement phases prior to motor execution and how this activity changes with visuomotor learning was particularly studied [2–7]. Importantly, visuomotor tasks require learning of an underlying mapping between the actual motor task space and the visual feedback environment [8], which further incorporates separate processing of different mapping aspects into the learning process [9, 10]. Hence, these studies generally quantify visual mapping performance together with motor execution skill, as visuomotor learning performance. We argue that such neuroimaging studies should dissociate learning of an underlying visual mapping from the pure motor learning process. In motor rehabilitation literature, motor learning, evaluated either in the form of motor adaptation or skill learning [11], is widely studied in force-field adaptation tasks [12, 13]. With this object in mind, we investigate how pre-movement EEG activity changes during pure motor learning without a separate artificial visual feedback environment, throughout a force-field adaptation task performed within an actual physical environment using a robotic setup.

Based on analysis of experimental data from fifteen healthy subjects, we observe a modulation of upper alpha (10–12 Hz) and lower beta (13–16 Hz) activity over the contralateral region during pre-movement phases throughout motor adaptation learning with the dominant hand. Moreover, through a statistical analysis of the recorded EEG signals and experimental data related to motor task performance, we demonstrate that this modulation is stronger in lower beta range and is associated with individual motor adaptation performances of subjects. Finally we propose to exploit these findings to potentially be used as a biomarker in novel stroke rehabilitation approaches by means of a brain-computer interface (BCI), which involves the idea of supporting motor recovery as well as inducing neural plasticity [14, 15].

2. METHODS

2.1. Subjects and Experimental Data

Fifteen right handed healthy subjects (10 male, 5 female; mean age 23.73 ± 3.03) participated in this study. All subjects were naive to the force-field adaptation task. Before the experiments, all participants gave their informed consent

after the experimental procedure was explained to them in accordance with guidelines set by the research ethics committee of Sabancı University.

Throughout the experiments, the robotic setup recorded data at 500 Hz sampling rate and a 64-channel EEG was recorded at 512 Hz sampling rate, using active EEG electrodes and a BioSemi ActiveTwo amplifier (Biosemi Inc., Amsterdam, The Netherlands). Electrodes were placed according to the 10-20 system. All data were re-referenced to common average reference offline.

2.2. Study Design

Participating subjects performed a force-field adaptation task under simultaneous EEG recordings with the goal of performing planar center-out reaching movements under an unknown force-field, as straightly as possible. During the experiments, subjects sat in front of a horizontally placed board, while holding an end-effector with their right hands that was suspended from above onto the board (see Figure 1). The end-effector was attached to a 3 degrees-of-freedom modified delta robot with constrained motion on z-axis and was only capable of two-dimensional movements that were restricted to fall within a circle with a radius of 200 mm. Idle starting position of the end-effector corresponded to the center of this circle. The four target locations placed on the circle at the northeast, northwest, southeast, and southwest positions were indicated with holes over the board containing LEDs inside.

Before the experiments, all subjects performed a pre-flight phase of eight trials (i.e., reaching movements) without any force-field to get familiar with the task workspace and trial flow. As part of the force-field adaptation task, each subject performed 200 trials in total, which were divided into three blocks of 40, 80, and 80 trials. Within each of these blocks, there were equal number of trials per target location. After the task, subjects also performed a washout phase of 20 trials which involved no force-field. Additionally, throughout the experiment, four blocks of five minute resting-state EEG recordings were performed; first resting-state recording before the force-field adaptation task, second recording after the
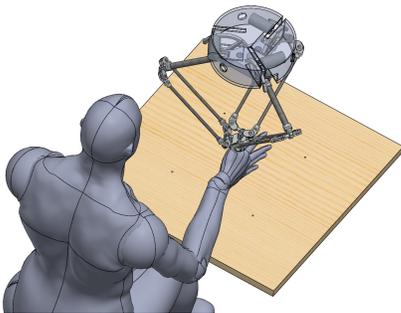

Fig. 1. Illustration of the task workspace. Four target locations are placed on the board, each at 200 mm distance.

first block of 40 trials, third recording at the end of the force-field adaptation task, and fourth resting-state recording after the washout phase. During these recordings, subjects were placed approximately 1.5 meters in front of a computer screen and instructed to relax with eyes open. Same experimental setup and data were also presented and used in our previous work for a different analysis [16].

2.3. Force-Field Adaptation Task

During reaching movements within the task workspace, a velocity dependent force-field was applied to the end-effector by the robotic setup. Specifically, end-effector velocity vector $\vec{v}$ was multiplied with a constant matrix $\mathbf{B}$, representing the viscosity of the imposed environment, to compute $\vec{f} = \mathbf{B}\vec{v}$ at each time point, where $\vec{f}$ represented the forces that the robotic setup is programmed to produce on the end-effector as the subject performed reaching movements. The constant matrix $\mathbf{B}$ was the same as in [17].

Each trial began with a *planning* phase, where the subjects were instructed to hold the end-effector at the starting position and plan the upcoming movement. The *planning* phase lasted 2.5–3.5 seconds, chosen randomly from a uniform distribution. Within the first second of this phase, the robotic setup assisted the subjects to center the end-effector position and directed the end-effector to the pre-calibrated starting position. During the *planning* phase, one of the four possible targets was selected by the system randomly and indicated by a blinking LED light. Each trial began with a new target location. At the end of the *planning* phase, the LED turned on steadily, signaling the beginning of the *go* phase. The time interval after the first second, until the end of the *planning* phase is referred as the *pre-movement* phase.

In the *go* phase, subjects were instructed to reach for the target by moving the end-effector over the board. A trial was considered complete when the subject moved the end-effector to within 20 mm of the target or if the subject exceeded a time limit of 3 seconds. After the *go* phase, the subjects were instructed to move the end-effector back to the starting position. At the end of the trials, to quantify motor adaptation amount, a calculated auditory feedback *score* within a range of 0–100 was provided from a speaker. The *score* in each trial indicated how straight the movement trajectory was in the corresponding trial. The area between the curve defined by the movement trajectory and a straight line to the target served as the basis kinematic measure for the *score* [18]. Aim of the subjects was to increase the feedback *score* throughout trials.

2.4. EEG Artifact Correction

In order to identify and attenuate potential artifactual activity from the EEG as part of pre-processing, we employed independent component analysis (ICA) [19]. We pooled all resting-state EEG data from all subjects, by concatenating

high pass filtered data at 3 Hz, and separated this data into group-wise statistically independent components (ICs) that represent cortical patterns consistently found across all subjects. This was done by first transforming the data into 64 principal components and then running the SOBI-algorithm, which computes the ICs [20]. We inspected each IC's topography, spectrum and time-series manually and rejected those which were not of cortical origin [21]. We then reprojected the remaining ICs to the scalp.

2.5. Pre-Movement EEG Activity Modulation

Using the artifact-corrected EEG data, each subject's *pre-movement* activity (i.e., EEG signals extracted from the *planning* phase of each trial) was transformed into the spectral domain. Specifically, we computed spectral powers of data from each electrode during *pre-movement* as mean log-bandpowers in sixteen frequency sub-bands. Log-bandpowers were computed at center frequencies from 9 Hz to 24 Hz, in 3 Hz-wide bands, using an FFT in conjunction with a Hanning window of one second length and a step-size of 100 ms.

To observe any frequency sub-band specific modulation in data from any particular region of the head surface throughout the experiments, we computed mean log-bandpowers across all subjects, at each electrode and frequency sub-band during each trial. For each frequency sub-band, at each electrode, R^2 between mean log-bandpowers at each trial and temporal order of 200 trials was computed. A higher R^2 value denoted a stronger modulation of activity at that particular electrode. Then, for each frequency sub-band, R^2 values corresponding to each electrode was displayed as a modulation topography.

2.6. Relation of Modulation with Motor Adaptation

Frequency sub-bands and electrodes that showed modulation on the topographies were further inspected on whether this pre-movement modulation is associated with motor adaptation learning on a subject-specific level. For this purpose, firstly motor adaptation performance was quantified with four different kinematic measures in every trial of all subjects: (1) auditory feedback *scores*, (2) total area between the curve defined by the movement trajectory and a straight line to the target, (3) maximum deflection from the straight line path to the target during movement, (4) coefficient of determination between vertical and horizontal position vectors during reaching movement.

Then, all electrodes and frequency sub-bands that showed modulation were investigated individually for each subject on whether any of those activities is correlated with motor adaptation across trials. Specifically, the four kinematic measures computed at each trial served as the independent variables to a multivariate linear regression model and measured electrode sub-band powers at each trial served as the dependent variables, to predict EEG powers for 200 trials. For every subject, the electrode and frequency sub-band pair that showed maximum R^2 between measured electrode sub-band powers and the corresponding model's predicted EEG powers across 200 trials was determined. Significance of this R^2 was tested with a random permutation test. To test the null-hypothesis of zero correlation, we randomly permuted the assignment of kinematic measures to EEG powers across trials 10,000 times and estimated the frequency at which the prediction model achieved a higher R^2 than with the true assignment of EEG powers to kinematic measures as the p-value.

3. RESULTS

Modulation topographies across frequency sub-bands with center frequencies from 9 Hz to 24 Hz showed apparent modulation in upper alpha (10–12 Hz) and lower beta (13–16 Hz) frequencies over the contralateral region (see Figure 2). This modulation was stronger and significant in lower beta range; highest for electrode C1 at sub-band center frequency 15 Hz ($R^2 = 0.16$, $p < 10^{-3}$ for a random permutation test). Here, the correlation coefficient between mean log-bandpowers and temporal order of trials was positive ($\rho = 0.40$), indicating an increase of activity rather than a suppression.
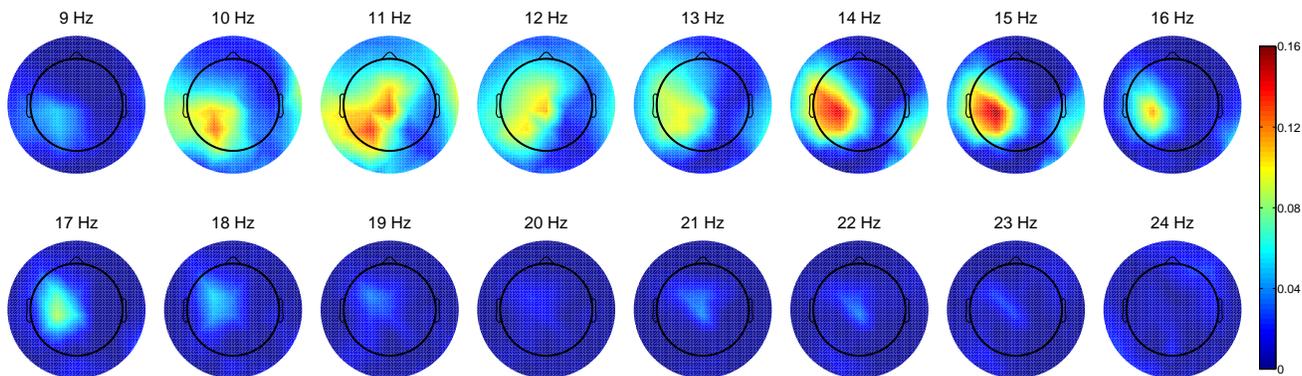

Fig. 2. Modulation topographies of bandpowers in 3 Hz-wide sub-bands with center frequencies ranging from 9 Hz to 24 Hz.

Table 1. Subject-level most significant results of R^2 values between motor adaptation performance and modulation in low beta sub-bands over the contralateral region.

Subjects	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
Electrode Location	CP5	C3	C1	FC1	CP3	CP5	CP1	FC1	CP5	FC5	CP1	C1	CP1	CP1	FC1
Center Frequency (Hz)	15	13	16	14	15	15	14	13	14	15	15	16	13	13	13
R-Squared (R^2)	**0.05***	**0.05***	0.03	0.04	**0.05***	**0.07**†	**0.06***	**0.06***	**0.05***	0.04	0.04	**0.06***	**0.17**†	0.03	**0.07**†

$^*\, p < 0.05$, $^\dagger\, p < 0.01$

Based on this initial analysis, six electrodes over the contralateral region (C1, C3, C5, CP1, CP3, CP5, FP1, FP3, FP5 sites from the 10-20 electrode placement system [22]) in four frequency sub-bands in low beta range (with center frequencies from 13 Hz to 16 Hz) were selected for subject-specific analyses on the relation of EEG activity modulation and motor adaptation learning. For each subject, the electrode and frequency sub-band pair with highest R^2 values among these are presented in Table 1 with the corresponding *p*-values. Ten out of fifteen subjects showed specific pre-movement low beta activity over the contralateral region that is significantly correlated with trial-wise motor adaptation performance. Moreover, we observe that a whole low beta band (13–16 Hz) modulation topography of the mean activity over these ten subjects showed stronger modulation than the other five subjects' mean activity modulation topography (see Figure 3).

4. DISCUSSION

In this study we implemented a force-field adaptation task with simultaneous EEG recordings to study the changes in neural activity during motor adaptation learning. The task was performed within an actual physical environment as distinct from conventional neuroimaging studies based on visuomotor learning tasks. Using an ICA-based artifact removal procedure and an EEG signal processing pipeline, we observed a modulation of contralateral upper alpha and lower beta powers throughout motor adaptation learning, which was strongly evident for lower beta range. Moreover using a multivariate linear regression approach, we present that this modulation is associated with motor learning on a subject-specific level. This demonstrates that it might be possible to predict motor learning performance from EEG data.

We argue that these findings can be used as a biomarker for current BCI-assisted stroke rehabilitation approaches. In such protocols, BCIs are often used to decode movement intent from EEG data that is synchronized to a rehabilitation robot with haptic feedback to provide movement support during rehabilitation exercises [23–25]. Similarly during rehabilitation exercises a BCI can monitor the EEG of the patient, and provide movement support whenever an individually spatially and spectrally characterized increase of pre-movement EEG activity is detected, with the goal of supporting motor learning. This artificial neurofeedback loop can possibly further incorporate adaptive approaches as proposed in [26], or likewise studied in [27, 28]. However, whether reinforcing this change in pre-movement activity by such rewards would indeed support motor recovery of stroke patients remains as an interesting question inspired by the study presented here.

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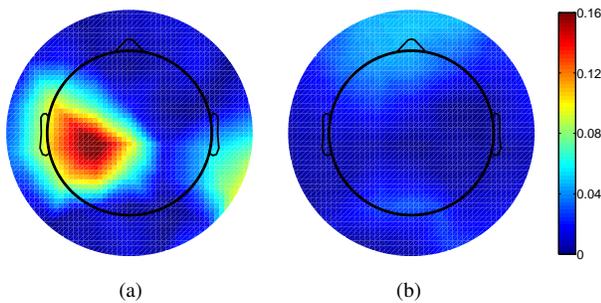
Fig. 3. Low beta modulation topographies for mean activity of the: (a) ten subjects with significant correlation between modulation and motor performance, (b) other five subjects.

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