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# CORRELATIONS OF MOTOR ADAPTATION LEARNING AND MODULATION OF RESTING-STATE SENSORIMOTOR EEG ACTIVITY

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ABSTRACT: There exists a variety of electroencephalogram (EEG) based brain-computer interface (BCI) assisted stroke rehabilitation protocols which exploit the recognized nature of sensorimotor rhythms (SMRs) during motor movements. For novel approaches independent of motor execution, we investigate the changes in resting-state sensorimotor EEG with motor learning, resembling the process of post-stroke recovery. In contrast to the neuroimaging studies based on visuomotor tasks, we study motor learning during an actual physical motor adaptation learning experiment. Based on analysis of EEG data collected throughout a force-field adaptation task, we observed a spectral power increase of resting SMRs across subjects. The modulation across resting-states in an early adaptation phase of the motor task was further shown to predict individual motor adaptation performance measures.

## INTRODUCTION

Over the last few decades, EEG activity of the human sensorimotor cortex is widely targeted as a biomarker in BCI-assisted stroke rehabilitation protocols to support motor restoration and induce neural plasticity $[1-3]$. In general, these approaches utilize congruent haptic feedback of neurally decoded movement intent through SMRs, by a rehabilitation robot $[4-6]$, and were shown to support modulation of SMRs during training and enhance post-stroke recovery [7]. Stroke recovery involves a form of motor learning, which has also motivated studies aimed at gaining insights into the neural processes underlying human motor behavior [8]. In this context, various brain imaging studies focus on analyzing recorded neural data during motor learning experiments [9, 10]. However, motor learning related sensorimotor activity changes in the resting brain, independent of motor execution, are yet to be studied.

Within this scope, several pieces of previous work have studied the concept of visuomotor learning $[11-13]$. However visuomotor tasks generally require learning of an underlying mapping between the actual motor task space and the visual feedback environment. Hence as a confounding factor, this further incorporates separate processing of different visual mapping aspects into the learning process [14, 15]. We argue that such neuroimaging studies should dissociate learning of an underlying visual mapping from the pure motor learning process. Conventionally in motor rehabilitation literature, motor learning is studied either in the form of motor adaptation or skill learning [16], particularly with force-field adaptation tasks [17, 18]. Accordingly, we investigate resting-state sensorimotor EEG changes with pure motor learning during a force-field adaptation task performed within an actual physical environment using a robotic setup, without a separate artificial visual feedback environment.

Based on statistical analysis of experimental data from twenty-one healthy subjects, we observed an increase of resting-state $\alpha$-band (8–14 Hz) sensorimotor activity across subjects throughout motor learning. Moreover, regression analysis demonstrates that the amount of the observed increase in sensorimotor activity across resting stages in an early adaptation phase of the motor task is predictive of individual motor adaptation learning performances. Finally we discuss how these motor learning related changes in resting-state EEG can be exploited in future BCI-assisted stroke rehabilitation protocols.

## MATERIALS AND METHODS

*Subjects and Experimental Data:* Twenty-one right handed healthy subjects (14 male, 7 female; mean age 23.8 ± 3.1) 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.

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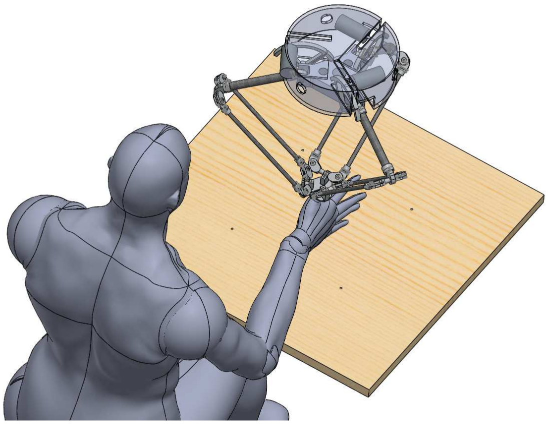


Figure 1: Illustration of the task workspace. Four target locations are placed on the board at the northeast, northwest, southeast, and southwest positions with equal distances of 200 mm from the center.

*Study Design:* Participating subjects performed a force-field adaptation task under simultaneous EEG recordings. The goal of the task was learning to perform 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 constructing the task workspace. Subjects were holding a handle, henceforth referred to as an end-effector, with their right hands that was suspended from above onto the board. The end-effector was attached to a 3 degrees-of-freedom modified delta robot which had 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. There were four target locations placed on the circle at the northeast, northwest, southeast, and southwest positions. The target locations were indicated with holes over the board containing LEDs inside. An illustration of the task workspace is provided in Fig. 1.

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.

In order to investigate the changes in resting-state sensorimotor activity with motor adaptation learning, alongside the force-field adaptation task, five-minute resting-state EEG recordings were performed throughout the experiment. First resting-state recording was performed before the force-field adaptation task, second recording after the first block of 40 trials and a third resting-state recording after completion of the force-field adaptation task. During these recordings, subjects were placed approximately 1.5 meters in front of a computer screen and instructed to relax with eyes open, looking at a fixation cross displayed in the middle of the screen. Resting-state recordings were performed with subjects' eyes open to construct a baseline condition for the force-field adaptation task that involved visual processing [19]. Same experimental setup and data were also presented and used in our previous work for different analyses [20, 21].

*Force-Field Adaptation Task:* The task involved two-dimensional center-out reaching movements within the task workspace, while a velocity dependent external force-field was applied to the end-effector by the robotic setup to disturb subjects' motions. 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 [22].

Throughout the experiments, subjects performed 200 trials with a randomized order of 50 trials for each of the four target locations. At the beginning of each trial, the target location was indicated with a blinking LED light. As the subject reached for the target location using the end-effector and then moved back to the starting position, a calculated *score* within a range of 0–100 was read out to the subject through a speaker. The *score* in each trial indicated how straight the movement trajectory was in the corresponding trial. To calculate the *score*, we first computed the sum of perpendicular distances of each point on the movement trajectory to the ideal path (i.e., straight line from center to target) [23]. Secondly, this sum served as an input variable to a sigmoid function, indicating a gradually diminishing increase [24]. Third, the value of the sigmoid function was multiplied by the elapsed time of the trial as a penalty on the *score*. At the end of each trial, the subjects were informed about their movement performance by inversely mapping this value to a range of 0–100; a higher *score* denoting a faster and more straight reaching movement. Aim of the subjects was to increase the *score* throughout trials.

*Resting-State Sensorimotor EEG Processing:* For all analyses in this study, from the 64-channel EEG data recorded during the experiments, we only used the C3, CP3, C4, and CP4 electrodes that are known to mainly represent sensorimotor activity of the brain [25 − 28]. As each resting-state five-minute time-series data constituted a high dimensional matrix (4 channels x 153600 samples), we implemented dimensionality reduction in the temporal domain. Specifically, we transformed EEG data of each electrode into the spectral domain and computed log-bandpowers in four main frequency bands; $\theta$-band (4–7 Hz), $\alpha$-band (8–14 Hz), $\beta$-band (15–30 Hz), and $\gamma$-band (55–85 Hz). We computed resting-state log-bandpowers using an FFT in conjunction with a Hann window spanning the whole five-minute resting phase. This analysis resulted in resting-state powers in four main frequency bands and four electrodes for each subject.

*Changes in Resting Sensorimotor Activity:* We used a Wilcoxon signed-rank test to investigate if there is a significant frequency-specific change in the resting-state sensorimotor activity across subjects from first to the second resting-state with an early adaptation, or from first to third resting-state throughout the complete adaptation period. In particular, for all frequency bands and four electrodes separately, differences of bandpower values between first and second resting-state recordings, and first and third resting-state recordings were computed and was used to test the null hypothesis of zero median across twenty-one subjects.

*Relation with Motor Adaptation Learning:* Resting-state sensorimotor activities that showed significant power changes across subjects were further inspected on whether these changes are related with the motor adaptation learning process. As trial-to-trial variability in performance is not of interest in this context, individual rate-based motor adaptation learning metrics were quantified from the feedback *scores* for each subject. Specifically, in order to represent an early motor adaptation learning performance in the first block of 40 trials, where the initial exposure to the force-field occurs, the ratio of average *scores* of the first ten trials over average *scores* of the last ten trials of the first block is computed. Similarly to represent the complete adaptation period, the ratio of average *scores* of the first ten trials over average *scores* of the last ten trials of the whole experiment is computed. A smaller value of these metrics indicates greater motor adaptation in the corresponding time period. These measures served as the dependent variables in separate multivariate linear regression models, where the changes in resting sensorimotor activity were used to predict learning performance in the corresponding time period.

Before regression analyses, we checked all subjects' performance measures and EEG features on whether it exceeded three standard deviations of the median across subjects, as an outlier rejection criterion. The differences of the four electrode powers between the first and the second resting-state blocks served as the independent variables to the regression model to predict early motor adaptation learning rates using a leave-one-subject-out cross-validation protocol. Similarly the differences between first and third resting-state EEG features were used to predict the complete adaptation learning metrics.

*Statistical Significance Testing:* To quantify the strength of a prediction model, the correlation coefficient between actual and predicted performance measures was computed. Significance of this correlation was tested with a permutation test. To test the null-hypothesis of zero correlation, we randomly permuted the assignment of performance measures to EEG features across subjects 10,000 times and estimated the frequency at which the prediction model achieved a higher correlation coefficient than with the true assignment of EEG features to performance measures as the $p$-value.

## RESULTS

Obtained $p$-values of the Wilcoxon signed-rank tests on potential frequency-specific changes of resting-state electrode bandpowers across subjects from first to the second resting-state with early adaptation, or from first to third resting-state with complete adaptation, are given in Tab. 1. In particular, we observe a significant increase of $\alpha$-powers across twenty-one subjects in all four electrodes (C3, CP3, C4, and CP4) located over sensorimotor areas (i.e., SMRs) with early adaptation. Moreover, this across-subjects increase in SMR activity is preserved in C3 and CP4 electrodes, but not still statistically significant in CP3 and C4 ($p = 0.06$) after the experiment, with complete adaptation. We do not consider the other two statistically significant $p$-values obtained by the electrode C3 as notable due to lack of consistency. For all four electrodes, resting-state $\alpha$-power levels of all subjects and the mean across subjects are presented in Fig. 2, mainly showing an increase of $\alpha$-powers resulting in the significant $p$-values of Tab. 1.

Subjects explicitly show motor adaptation learning effects in terms of the feedback *score* metric they are provided (see Fig. 3a). In particular, we observe that most of the adaptation occurs in the first block of 40 trials with the initial exposure to the force-field. Investigating the relation between the observed resting-state $\alpha$-power changes and individual adaptation rates, the early adaptation linear regression model shows statistically significant results. Specifically, the differences of the four electrode $\alpha$-powers between the first and the second resting-state blocks (i.e., through early adaptation) of the subjects were found predictive of individual early adaptation learning rates, which span a wide range of performance measures across subjects ($\rho = 0.55, p < 0.01$, see Fig. 3b and 3c). On the other hand, difference of $\alpha$-powers between the first and third resting-state recordings was not able to predict the complete adaptation learning rate metrics ($\rho = -0.30, p > 0.05$).

Table 1: $p$-values of the Wilcoxon signed-rank test on observed changes of bandpower activity in the early or complete adaptation phases across subjects. Colored cells indicate statistically significant results ($p \leq 0.05$).

| **Bandpower** | **Adaptation** | **C3** | **CP3** | **C4** | **CP4** |
|---|---|---|---|---|---|
| $\theta$-band | Early | 0.01 | 0.37 | 0.90 | 0.15 |
| | Complete | 0.76 | 0.47 | 0.56 | 0.98 |
| $\alpha$-band | Early | 0.03 | 0.01 | 0.04 | 0.05 |
| | Complete | 0.02 | 0.06 | 0.06 | 0.05 |
| $\beta$-band | Early | 0.84 | 0.52 | 0.76 | 0.33 |
| | Complete | 0.04 | 0.06 | 0.09 | 0.66 |
| $\gamma$-band | Early | 0.47 | 0.82 | 0.68 | 0.59 |
| | Complete | 0.41 | 0.18 | 0.16 | 0.45 |

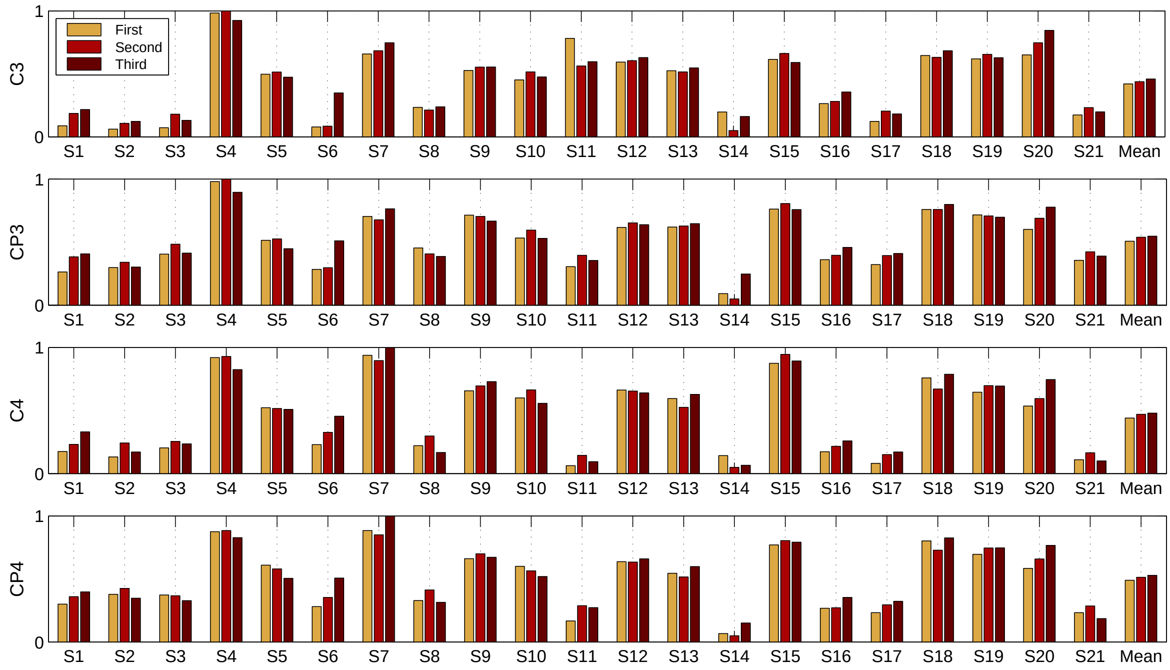
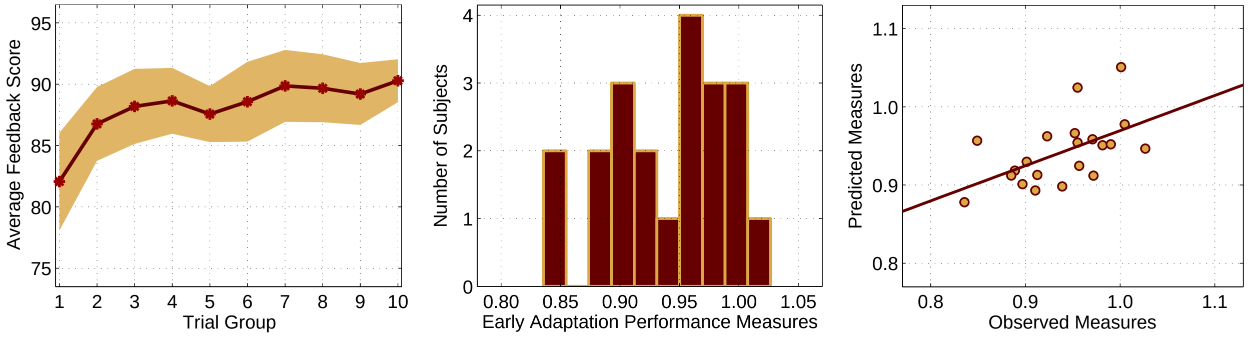


Figure 2: Normalized $\alpha$-power levels of the four electrodes during three resting-state recordings of all subjects. Mean $\alpha$-powers across subjects are presented at the rightmost slot.

# DISCUSSION

In this study, we investigate resting-state changes in sensorimotor EEG activity throughout motor adaptation learning by a force-field adaptation task. The task was performed within an actual physical environment to discard any visual mapping confounders that potentially exist in most visuomotor task based neuroimaging studies. Subjects showed apparent motor performance increases throughout the task. We observed explicit increase in resting-state $\alpha$-powers across subjects both after an early adaptation and after the adaptation was complete. Moreover, the changes in resting $\alpha$-power was found predictive of individual measures of distinct adaptation rates during an early adaptation time period of the experiment.

We hypothesize that the observed SMR-power increase across subjects, which is mostly evident after an early adaptation, is likely to indicate a cortical reorganization of the SMR activity. Even though there exist a variety of studies indicating the relation of SMRs and human motor behavior, a non-invasive neuroimaging based evidence on resting activity modulations was not reported with a pure motor learning task before. While the continuity of these resting-state changes for longer durations is not established on one hand, on the other hand, these results can be further exploited in novel stroke-rehabilitation paradigms



(a) (b) (c)

Figure 3: (a) Average subject feedback *scores* learning curve. Trial groups represent the sequential order of the 200 trials grouped in 20 trials each. Each point on the red curve represents an average *score* of 20 trials. Shaded region indicates the standard deviation. (b) Distribution of the early adaptation performance measures used in regression across subjects. (c) Observed versus predicted performance measures of the early adaptation regression model ($\rho = 0.55, p < 0.01$). One dot represents one subject.

that can potentially incorporate neurofeedback [29] or stimulation based alterations of the electrical activity of the brain [30, 31] by subject specific SMR localization. With a similar approach, several studies have previously focused on BCI-based sensorimotor training to improve motor behavior during a reaction-time task [27] or a joystick-based cursor-movement task [28]. Nevertheless, it is important to note that the evidence presented here is not sufficient to claim that modulating such brain activity ensures an increase in motor learning performance [32]. The present work solely focuses on investigating SMR activity, however we have recently studied EEG correlates of motor adaptation learning in a broader range of brain regions both during resting-state and movement preparation phases with a different analysis approach on this collected data [33]. These evidences can potentially be exploited in mentioned novel BCI-assisted stroke rehabilitation protocols.

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