

Resting-State EEG Correlates of Motor Learning Performance in a Force-Field Adaptation Task

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Abstract—Recent BCI-based stroke rehabilitation studies focus on exploiting information obtained from sensorimotor EEG activity. In the present study, to extend this focus beyond sensorimotor rhythms, we investigate associative brain areas that are also related with motor learning skills. Based on experimental data from twenty-one healthy subjects, resting-state EEG recorded prior to the experiment was used to predict motor learning performance during a force-field adaptation task in which subjects performed center-out reaching movements disturbed by an external force-field. A broad resting-state beta-power configuration was found to be predictive of motor adaptation rate. Our findings suggest that resting EEG beta-power is an indicator of subjects' ability to learn new motor skills and adapt to different sensorimotor states. This information can be further exploited in a novel BCI-based stroke rehabilitation approach we propose.

Index Terms—brain-computer interfaces; EEG; resting-state; motor learning; force-field adaptation

I. INTRODUCTION

Electroencephalogram (EEG) based brain-computer interfaces (BCIs) are used for direct brain communication in paralysis and motor restoration in stroke [1]. Utility of BCI technology in stroke rehabilitation gained particular interest arguing that it reinforces neural plasticity and supports motor recovery [2], [3]. In such protocols, BCIs are often used to decode movement intent from sensorimotor rhythms that is synchronized to a rehabilitation robot with haptic feedback [4], [5], [6]. Providing sensorimotor feedback has been shown to support modulation of sensorimotor rhythms and enhance post-stroke recovery [7]. Motivated by these results and considering the relevance of a variety of brain rhythms beyond sensorimotor areas to the extent of motor deficits [8], [9], we propose to extend the current focus of BCI-based stroke rehabilitation beyond sensorimotor rhythms to also include associative brain areas.

Stroke recovery is a form of motor learning [10]. Hence, identifying the large-scale cortical networks involved in motor learning is of importance in this context. To that end, the relation of resting-state EEG and motor learning; either in the form of motor adaptation or skill learning [11], should be investigated. In the next step, understanding how stroke-related disturbances of these resting-state networks relate to motor deficits would in turn yield knowledge about how these

networks can be exploited in a BCI-based rehabilitation setting. Particularly, a healthy reconfiguration of these networks via neurofeedback training, as proposed in [12], is likely to support motor recovery. With a similar approach, several studies have previously focused on BCI-based sensorimotor training to improve motor behavior during a reaction-time task [13] or a joystick-based cursor-movement task [14].

In this study, we address the issue of identifying resting-state EEG correlates of motor learning in a force-field adaptation task. Based on experimental data from twenty-one healthy subjects, we show that resting-state EEG recorded prior to the experiment can be used to predict motor adaptation with features extracted in the β -band. These findings are consistent with studies on the relation of broad β -activity and motor maintenance.

II. METHODS

A. Subjects

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.

B. Study Design

The 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. Using the task workspace, the subjects performed the force-field adaptation task (see section II-C) with simultaneous EEG recordings. The goal of the task was to perform center-out reaching movements under an unknown force-field, as straightly as possible. The end-effector was only capable of two-dimensional movements that were restricted to fall within a circle with a radius of 200 mm. Idle 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

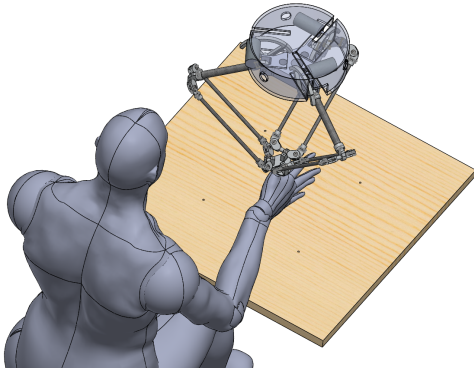


Fig. 1. Illustration of the task workspace. Four target locations are placed on the board (with equal distances of 200 mm from the center).

the board containing LEDs inside. An illustration of the task workspace is provided in Figure 1.

All subjects performed a pre-flight phase of eight trials before the experiments 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. Alongside the force-field adaptation task, four blocks of resting-state EEG recordings were performed throughout the experiment, each lasting for five minutes. During resting-state recordings, subjects were placed approximately 1.5 meters in front of a computer screen. The subjects were instructed to relax with eyes open, looking at a fixation cross displayed in the middle of the screen. Flow of the experiment is presented in Figure 2.

C. Force-Field Adaptation Task

The force-field adaptation task involved two-dimensional center-out reaching movements. Goal of the subjects was to follow a straight line path from starting position to the target location. During reaching movements, subjects' motions were disturbed by an external force-field. 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 [15]. During pre-flight and washout phases the subjects performed the reaching movements without an external force-field disturbance, but with the same trial flow.

Each trial began with a *planning* phase, where the subjects were instructed to hold the end-effector at the starting position (i.e., center of the circle on the board) and plan the upcoming movement. During this phase, one of the four possible targets is selected randomly and indicated by a blinking LED light. The *planning* phase lasted 2.5–3.5 seconds, chosen randomly from a uniform distribution. At the end of the *planning* phase, the LED turned on constantly, signaling the beginning of the *go* phase. In the *go* phase, the subjects were instructed to reach for the target by moving the end-effector over the board. The 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 s. 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 *score* within a range of 0–100 was read out to the subjects through a speaker. Each trial began with a new target location. Among a total of 200 trials, the number of trials corresponding to each of the four targets were equal.

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). Secondly, this sum served as an input variable to a sigmoid function, indicating a gradually diminishing increase [16]. 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*.

D. Experimental Data

Throughout the experiments, the robotic setup recorded data at 1 kHz 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.



Fig. 2. Flow of the experiment. Before the experiment the subjects performed a pre-flight phase. Green blocks indicate four resting-state recordings each lasting for five minutes. Red blocks indicate three blocks of force-field adaptation task which in total consisted of 200 trials. Before the fourth resting-state recording, the subjects performed a washout phase of 20 trials. Blocks are separated by brief intermissions of one to two minutes.

E. Resting-State EEG Analysis

Feature space to predict motor adaptation was obtained by first transforming the resting-state EEG recordings into a small number of relevant features. This was achieved by reducing the dimensionality of the EEG data. Specifically, 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). This was done by first reducing the data into 64 principal components and then running the SOBI-algorithm [17]. We inspected each IC manually and rejected those which were not of cortical origin [18]. The remaining six IC topographies are shown at the bottom row of Figure 5. We then computed resting-state log-bandpowers of each non-artifactual IC in θ - (4–7 Hz), α - (8–14 Hz), β - (15–30 Hz) and γ - (55–85 Hz) bands of all subjects, using an FFT in conjunction with a Hanning window. These bandpowers served as a feature space to a multivariate linear regression model to predict motor adaptation of the subjects.

F. Motor Adaptation Prediction

In order to monitor learning effects, we recomputed auditory feedback scores offline. Individual motor adaptation performance measures were extracted from scores of the first block of 40 trials, where the initial exposure and most of the adaptation to the force-field occurs. Specifically for each subject, the ratio of average scores of the first ten trials over average scores of the last ten trials of the first block is computed. These motor adaptation performance measures served as the dependent variable for a multivariate linear regression model.

Each subject’s six IC log-bandpowers in one of the four frequency bands from the first resting-state block were used as independent variables in the multivariate linear regression model to predict motor adaptation using a leave-one-subject-out cross-validation protocol. Prediction was done for all frequency bands to investigate if any resting-state neural correlates exist for motor adaptation performance in a particular frequency band. For each frequency band, to quantify the strength of the 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 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 brain rhythms to performance measures as the p -value.

III. RESULTS

The change in grand average scores was investigated to observe motor learning effects. As we were interested in a general improvement rather than trial-to-trial changes in score, we plotted 20-trial-averaged subject scores which followed a power law (see Figure 3).

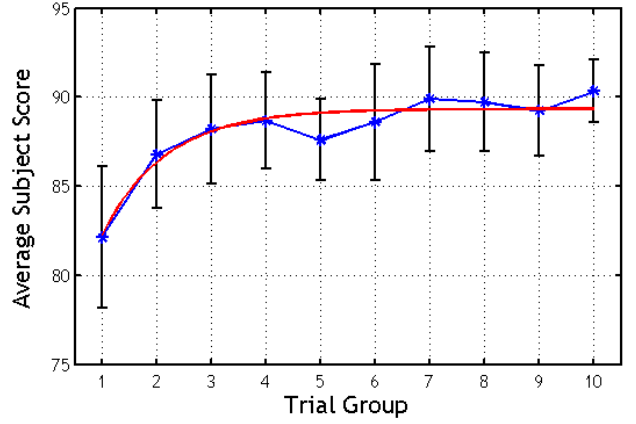


Fig. 3. 20-trial-averaged subject scores. Trial groups represent the sequential order of the 200 trials grouped in 20 trials each. Each point on the blue curve represents an average score of 20 trials. Error bars indicate standard deviation across subjects. Red curve is the exponential fit using nonlinear Nelder-Mead least-squares regression in the form $S_i = Ae^{i/\tau} + C$, where S_i is the score for trial group i , A represents the amount of learning, τ is the time-constant, and C represents the steady-state value.

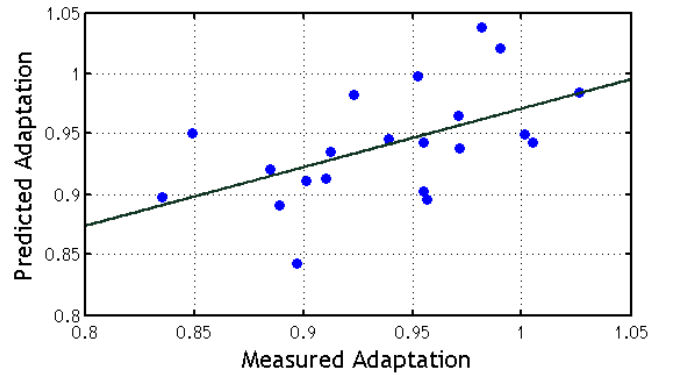


Fig. 4. Measured versus predicted motor adaptation performance measures for the β -band linear regression model. One dot represents one subject.

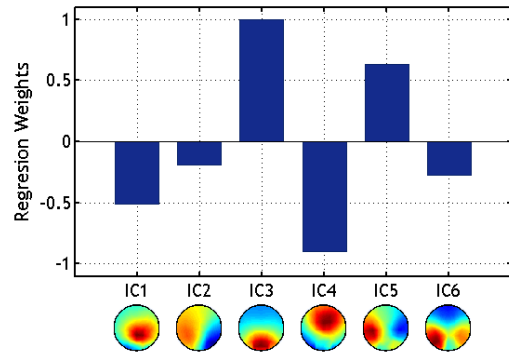


Fig. 5. Normalized weights of the β -band regression model for each IC. Topographies of the six non-artifactual ICs used for prediction are shown in the bottom row.

Investigating the correlation coefficients between actual and predicted performance measures, we observed that the prediction models did not provide statistically significant results in θ -band ($\rho = -0.0208$, $p = 0.58$), α -band ($\rho = 0.2477$, $p = 0.15$) or γ -band ($\rho = -0.2153$, $p = 0.33$). Using resting-state features extracted in β -band, we significantly predicted motor adaptation performance ($\rho = 0.5363$, $p = 0.02$, see Figure 4). Significance decreased in comparison to a single β -band prediction, if pairs of frequency bands were used as features in the regression model (e.g., both α - and β -powers as features: $\rho = 0.4736$, $p = 0.05$). Figure 5 shows linear regression weights of each IC, averaged over all cross-validation folds, for the β -band prediction model. Regarding the weights, we claim that most informative features are observed in cortical areas that are likely to represent sensorimotor processes (IC 5) and areas linked to fronto-parietal attention networks (ICs 1, 3, 4) [19].

IV. DISCUSSION

We have presented empirical evidence that resting-state EEG recorded prior to the experiment can be used to predict motor adaptation in a force-field adaptation task. Using β -powers of resting-state ICs as features in a multivariate linear regression model, significant prediction of the improvement rate of feedback scores in the first block of the experiment was obtained. Our results on relevance of a broad β -band activity is consistent with evidence in literature suggesting a causal influence of multiple cortical sources on motor learning performance [20]. Moreover, previous studies claim that a broad β -band network is informative of mechanisms related to motor maintenance [21], [22]. This further supports reliability of our findings on motor adaptation as a form of a change in current or upcoming sensorimotor state. Nonetheless, it is noteworthy that even though this study suggests significant results for a continuous force-field case, these results may not be extended to sudden or gradual force-fields, which are likely to tap into different brain processes [23].

Previously, relation of brain activities beyond primary sensorimotor areas and visuomotor learning performance were investigated [24], [25]. Here, we separate the motor learning task from additional visual processing. We claim that a broad resting-state β -band activity contributes to performance during a purely motor learning task in healthy subjects. Once we can translate these findings to stroke patients, in the context of our novel approach to BCI-based stroke rehabilitation, a further phase would be to investigate how these resting-state networks are disturbed due to stroke and how it relates to motor deficits. Then using BCI-based neurofeedback as a tool, a healthy reconfiguration of these networks can be obtained to support post-stroke motor recovery.

REFERENCES

- [1] N. Birbaumer and L. G. Cohen, "Brain-computer interfaces: communication and restoration of movement in paralysis," *The Journal of Physiology*, vol. 579, no. 3, pp. 621–636, 2007.
- [2] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," *The Lancet Neurology*, vol. 7, no. 11, pp. 1032–1043, 2008.
- [3] M. Grosse-Wentrup, D. Mattia, and K. Oweiss, "Using brain-computer interfaces to induce neural plasticity and restore function," *Journal of Neural Engineering*, vol. 8, no. 2, p. 025004, 2011.
- [4] M. Saraç, E. Koyaş, A. Erdoğan, M. Çetin, and V. Patoğlu, "Brain computer interface based robotic rehabilitation with online modification of task speed," in *IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2013, pp. 1–7.
- [5] M. Gomez-Rodriguez, J. Peters, J. Hill, B. Schölkopf, A. Gharabaghi, and M. Grosse-Wentrup, "Closing the sensorimotor loop: haptic feedback facilitates decoding of motor imagery," *Journal of Neural Engineering*, vol. 8, no. 3, p. 036005, 2011.
- [6] T. Meyer *et al.*, "A brain-robot interface for studying motor learning after stroke," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2012, pp. 4078–4083.
- [7] A. Ramos-Murguialday *et al.*, "Brain-machine interface in chronic stroke rehabilitation: A controlled study," *Annals of Neurology*, vol. 74, no. 1, pp. 100–108, 2013.
- [8] S. P. Finnigan, M. Walsh, S. E. Rose, and J. B. Chalk, "Quantitative EEG indices of sub-acute ischaemic stroke correlate with clinical outcomes," *Clinical Neurophysiology*, vol. 118, no. 11, pp. 2525–2532, 2007.
- [9] N. Sharma, J.-C. Baron, and J. B. Rowe, "Motor imagery after stroke: relating outcome to motor network connectivity," *Annals of Neurology*, vol. 66, no. 5, pp. 604–616, 2009.
- [10] J. W. Krakauer, "Motor learning: its relevance to stroke recovery and neurorehabilitation," *Current Opinion in Neurology*, vol. 19, no. 1, pp. 84–90, 2006.
- [11] J. W. Krakauer and P. Mazzoni, "Human sensorimotor learning: adaptation, skill, and beyond," *Current Opinion in Neurobiology*, vol. 21, no. 4, pp. 636–644, 2011.
- [12] O. Özdenizci, T. Meyer, M. Çetin, and M. Grosse-Wentrup, "Towards neurofeedback training of associative brain areas for stroke rehabilitation," in *Proceedings of the 6th International Brain-Computer Interface Conference*, 2014.
- [13] C. Boulay, W. Sarnacki, J. Wolpaw, and D. McFarland, "Trained modulation of sensorimotor rhythms can affect reaction time," *Clinical Neurophysiology*, vol. 122, no. 9, pp. 1820–1826, 2011.
- [14] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, "Effects of training pre-movement sensorimotor rhythms on behavioral performance," *Journal of Neural Engineering*, vol. 12, no. 6, p. 066021, 2015.
- [15] R. Shadmehr and F. A. Mussa-Ivaldi, "Adaptive representation of dynamics during learning of a motor task," *The Journal of Neuroscience*, vol. 14, no. 5, pp. 3208–3224, 1994.
- [16] N. Leibowitz *et al.*, "The exponential learning equation as a function of successful trials results in sigmoid performance," *Journal of Mathematical Psychology*, vol. 54, no. 3, pp. 338–340, 2010.
- [17] A. Belouchrani, K. Abed-Meraim, J.-F. Cardoso, and E. Moulines, "A blind source separation technique using second-order statistics," *IEEE Transactions on Signal Processing*, vol. 45, no. 2, pp. 434–444, 1997.
- [18] A. Delorme *et al.*, "Independent EEG sources are dipolar," *PLoS one*, vol. 7, no. 2, p. e30135, 2012.
- [19] S. L. Bressler and V. Menon, "Large-scale brain networks in cognition: emerging methods and principles," *Trends in Cognitive Sciences*, vol. 14, no. 6, pp. 277–290, 2010.
- [20] S. Weichwald, T. Meyer, O. Özdenizci, B. Schölkopf, T. Ball, and M. Grosse-Wentrup, "Causal interpretation rules for encoding and decoding models in neuroimaging," *NeuroImage*, vol. 110, pp. 48–59, 2015.
- [21] A. K. Engel and P. Fries, "Beta-band oscillations – signalling the status quo?" *Current Opinion in Neurobiology*, vol. 20, no. 2, pp. 156–165, 2010.
- [22] A. Brovelli *et al.*, "Beta oscillations in a large-scale sensorimotor cortical network: directional influences revealed by Granger causality," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 101, no. 26, pp. 9849–9854, 2004.
- [23] M. Grosse-Wentrup and J. L. Contreras-Vidal, "The role of the striatum in adaptation learning: a computational model," *Biological Cybernetics*, vol. 96, no. 4, pp. 377–388, 2007.
- [24] T. Meyer, J. Peters, T. O. Zander, B. Schölkopf, and M. Grosse-Wentrup, "Predicting motor learning performance from electroencephalographic data," *Journal of NeuroEngineering and Rehabilitation*, vol. 11, no. 1, 2014.
- [25] J. Wu, R. Srinivasan, A. Kaur, and S. C. Cramer, "Resting-state cortical connectivity predicts motor skill acquisition," *NeuroImage*, vol. 91, pp. 84–90, 2014.