Towards Neurofeedback Training of Associative Brain Areas for Stroke Rehabilitation

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Abstract

We propose to extend the current focus of BCI-based stroke rehabilitation beyond sensorimotor-rhythms to also include associative brain areas. In particular, we argue that neurofeedback training of brain rhythms that signal a state-of-mind beneficial for motor-learning is likely to enhance post-stroke motor rehabilitation. We propose an adaptive neurofeedback paradigm for this purpose and demonstrate its viability on EEG data recorded with five healthy subjects.

1 Introduction

While initially conceived as communication devices for severely paralyzed patients, brain-computer interfaces (BCIs) have recently been considered in the context of post-stroke motor rehabilitation [1]. Here, BCIs are employed to synchronize movement intent, as decoded by a BCI from sensori-motor rhythms, with congruent haptic feedback, e.g., as delivered by an exoskeleton [2]. This artificial re-establishment of the sensorimotor feedback loop has been shown to support modulation of sensorimotor-rhythms [3] and result in enhanced post-stroke recovery [4]. In this paper, we argue that, motivated by the impressive results achieved to date, the current focus should be extended beyond sensori-motor- to also include associative brain areas. This argument is based on empirical evidence that a variety of brain rhythms beyond those in primary sensorimotor areas are related to the extent of post-stroke impairment. For instance, the global ratio of δ- to α-power of the brain's electromagnetic field has been found to correlate with the extent of post-stroke disability and predict subsequent recovery [5]. We interpret such abnormal activation patterns as disturbances of the balance of large scale cortical networks [6], and argue that re-establishing their natural balance by means of BCI-based neurofeedback is likely to support the brain in post-stroke recovery.

In order to turn this hypothesis into a viable stroke rehabilitation protocol, several interrelated problems need to be addressed. Firstly, we need to identify which large scale networks are involved in sensori-motor learning in healthy control subjects. Next, we have to investigate how activation patterns of and between these networks are disturbed in stroke patients, and elucidate how these disturbances relate to post-stroke recovery. And thirdly, we need to train patients via neurofeedback to establish activation patterns of large scale networks that are associated with good post-stroke recovery.

In the present work, we address the viability of the last issue. In a recent publication, we have identified EEG correlates of motor-learning performance [7]. In particular, we have provided evidence that parieto-occipital α-power during rest as well as during movement preparation predicts performance in a subsequent reaching movement. This led us to hypothesize that parieto-occipital α-power reflects activity in a cortical network that is tuned by the brain to optimize motor-learning performance. Here, we propose an adaptive neurofeedback training scheme to modulate parieto-occipital α-power in a way that we predict will enhance motor-learning performance. Based on experimental data from five healthy subjects we argue that, firstly, subjects are able to modulate parieto-occipital α-power by means of neurofeedback, and, secondly, that this modulation is not task-specific but extends into the inter-trial resting-periods. Taken together, these results indicate the feasibility of using neurofeedback to support subjects in generating brain activation patterns that are associated with good motor-learning performance. This constitutes an important building block towards a stroke therapy based on neurofeedback training of associative brain areas.

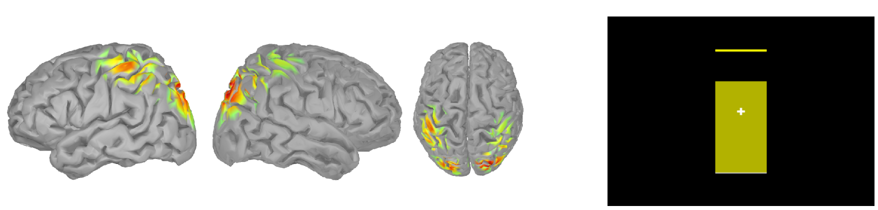
2 Methods

2.1 Experimental Data

Five healthy subjects were recruited for this study, each of which completed two training sessions. Each session lasted one hour with one week interval between sessions. Prior to the training sessions all participants gave their informed consent after the training procedure was explained to them in accordance with guidelines set by the Max Planck Society. During the training sessions, a 120-channel EEG was recorded at 1 kHz sampling rate, using active EEG electrodes and a QuickAmp amplifier (BrainProducts, Gilching, Germany). Electrodes were placed according to the 10-20 system, with Cz as the initial reference electrode. All data was re-referenced to common average reference.

2.2 Adaptive Online Feedback

Each training session included one resting-state baseline and eight training blocks with one minute breaks in between. For the resting-state baseline, subjects were instructed to relax for five minutes with eyes open, looking at a fixation cross displayed centrally on a screen approximately 1.5 m in front of the subjects. This resting-state data was used to calibrate the feedback for the subsequent training session. Specifically, the 120-dimensional raw EEG data $\boldsymbol{x}[t]$ was first spatially filtered by a filter $\boldsymbol{w}$ to obtain a one-dimensional signal $y[t] = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}[t]$. The spatial filter $\boldsymbol{w}$ was taken from a group-wise independent component analysis (ICA) of a previous study [7], in which the corresponding independent component's α-power was found to predict performance in a motor-learning task. Figure 1a displays the source localization results obtained for this independent component in parieto-occipital areas (adapted from [7]). Next, log-bandpower of the spatially filtered signal was computed in the α-band (8-14 Hz), using a FFT in conjunction with a Hanning window, in a sliding window of 2 s with a window step size of 100 ms. This signal processing pipeline was used to compute the mean and standard



(a) (b)

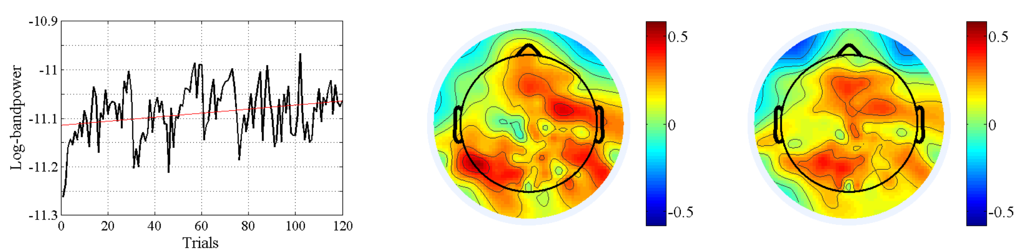
Figure 1: a) Parieto-occipital region used for neurofeedback [7]. b) Visual stimulus.

deviation of resting-state α-power.

In each training block, the same signal processing pipeline was used to provide subjects with visual feedback on parieto-occipital α-power. The current estimate of parieto-occipital α-power was displayed as the vertical height of a rectangular visual stimulus on the screen (Figure 1b), which was updated at 25 Hz. The bottom of the rectangle corresponded to the mean log-bandpower of the resting-state baseline. One training block consisted of 15 trials. In each trial, subjects were given the objective to increase the vertical height of the rectangle to reach an adaptively determined target height level marked by an upper bar on the screen. Subjects had to learn to up-regulate the presented brain activity with eyes open and keep the activity at that level or above for a cumulative time of two seconds. No instructions were given to the subjects on how to achieve this goal. If subjects succeeded in this task in a 15 second trial, the rectangle turned green. Otherwise, the next trial began after a short resting-period, with a randomly determined length between 4.5 to 5.5 seconds. For the first training block, the target distance was set to one standard deviation of the log-bandpowers in the resting-state baseline. Depending on the performance of the subject, the target distance changed. It increased by 0.2 standard deviations of the resting-state baseline phase in the next block, if the success rate of the previous block over 15 trials was higher than 70%. The target distance decreased by the same amount if the success rate was lower than 60%. This adaptive approach was implemented to balance any potential frustration or negligence of the subject on the task [8]. During the training sessions, presentation of the stimulus and real-time data processing was performed with the BCI2000 software [9] and its extension BCPy2000 [10].

2.3 Offline Data Analysis

Following the last training session, the data of all subjects and sessions was visually inspected for contamination by ocular artifacts. The data of one session of one subject was discarded, as it was heavily contaminated by eye blinks. To assess the overall effect of neurofeedback training, we then pooled the data of all subjects and sessions. Specifically, we computed the correlation of trial-number, ranging from one to 120, with parieto-occipital α-power, averaged across subjects and sessions, in each trial. In this way, we estimated the linear trend in parieto-occipital α-power across a training session. We also computed this correlation for α-power at each individual recording channel in order to investigate the topography of α-power modulation. Finally, we computed the same correlation only using the EEG data of the resting-periods prior to each trial.



(a) (b) (c)

Figure 2: a) Grand average of trial α-log-bandpower values (red is the linear fit). b) Topography of grand average log-bandpower correlations with trial numbers within a session of 120 trials in α-band (for trial phases). c) Same topography in (b) obtained for rest phases.

3 Results

Parieto-occipital α-power displays a positively-sloped linear trend within a training session of 120 trials (Figure 2a) with a correlation coefficient of $\rho = 0.26$. A permutation test on the temporal order of trials with 10^4 permutations rejected the null-hypothesis of zero correlation with $p = 0.002$ ($N = 120$). Correlation values between α-power and trial number at each individual electrode are shown in Figure 2b and 2c for trial- and pre-trial data, respectively. These results indicate that subjects learned to modulate parietal α-power and that this self-regulation extended beyond the actual feedback phase into the inter-trial resting phases.

4 Discussion

In this pilot study, we presented an adaptive neurofeedback training paradigm that enables subjects to up-regulate parieto-occipital α-power. Importantly, we could provide evidence that up-regulation of α-power was sustained in the inter-trial periods, indicating that subjects learned to induce a stable state-of-mind that we predict will be beneficial for motor-learning [7]. In future work, this training paradigm will be carried out by stroke patients prior to a rehabilitation session. We hypothesize that this will be beneficial for motor-learning and hence support post-stroke motor recovery.

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