Toward Comparison of Cortical Activation with Different Motor Learning Methods Using Event-Related Design: EEG-fNIRS Study

Hojun Jeong, Minsu Song, Seunghue Oh, Jongbum Kim and *Jonghyun Kim, *Member, IEEE*

Abstract—**Recently, motor imagery brain-computer interface (MI-BCI) has been studied as a motor learning method and evaluated by comparing with conventional passive and active training. Most functional near-infrared spectroscopy (fNIRS) studies adopted block design for comparing those motor learning methods, including MI-BCI. Compared to the block design, event-related design would be more appropriate for estimating cortical activation in MI-BCI which provides feedback for each trial. This paper is a preliminary study to check the feasibility whether event-related design can be applicable for MI-BCI. To this end, three different motor learning methods involving MI-BCI were compared. In hemodynamic response, MI-BCI showed significantly stronger cortical activation than passive training (PT), and weaker than active training (AT), which conforms most existing studies. The results demonstrate that event-related design could be applied to investigate cortical effects of MI-BCI and comparing hemodynamic responses of different motor learning methods.**

I. Introduction

Motor learning is a well-known strategy that has been around for a long time in rehabilitation. Conventional motor learning methods can be broadly classified into active training (AT), in which the user voluntarily moves the body, and passive training (PT), in which the user's body is moved by the clinician or the external devices, such as functional electrical stimulation or rehabilitation robot [1]. PT, which is applied to the patients who have difficulty in performing AT, is a method of training through continuous repetition. The limitation of PT is that the involuntary movement is just repeated regardless of the subject's intention [2]. To overcome this limitation, the motor imagery-based brain-computer interface (MI-BCI) has been reported for rehabilitation [3,4]. MI-BCI uses the devices which can obtain brain signal, mostly electroencephalogram (EEG), to provide movement feedback to the user's motor intention [5].

Based on the claimed statement that MI-BCI is more effective in terms of neurorehabilitation than conventional PT [6,7], some studies compared the conventional motor learning methods with MI-PT combination [8,9] to support this statement. However, MI-PT combination, a sham design of MI-BCI, cannot provide exact feedback due to motor imagery, and thus it is not possible to evaluate the motor imagery for each trial. As a solution to this problem, a study has reported the cortical effects of MI-BCI compared to conventional PT, but it lacks another motor learning, AT [10]. Moreover, those existing studies which used functional near-infrared spectroscopy (fNIRS) or functional magnetic resonance imaging (fMRI) did not estimate the individual event-related hemodynamic response function, closely related to the feedback loop of MI-BCI, to show cortical effects due to limitation of using block design paradigm.

The block design, which has been widely used in fNIRS and fMRI studies to estimate motor activation in the brain, is useful for measuring the hemodynamic response changes accumulated through the repetition of several motor activities [11]. On the other hand, event-related design paradigm, popularly used in EEG and fMRI studies, is beneficial to estimate temporal course of hemodynamic response function because it could capture temporal dynamics of a single stimulus-response. Hence, the event-related design would be more appropriate to compare the conventional motor learning methods with MI-BCI that provides feedback by detecting single event like motor imagery [12]. However, there is no study which uses the event-related design for this kind of comparison.

This is a preliminary study for validating feasibility that the event-related design can be applicable for MI-BCI, while we attempt to compare different motor learning methods (MI-BCI, PT, and AT). For that, we proposed the event-related fNIRS design to estimate the hemodynamic response function for a single trial of those methods. Furthermore, electrical signals were also measured through EEG to validate and compare how well the motor learning methods were performed. We hypothesized that the event-related design can be applicable for analyzing cortical effects of MI-BCI and for comparing hemodynamic responses as well as electrical brain signals of the motor learning methods simultaneously.

II. Methods

A. Participants

Seven healthy volunteers (5 males; age: 20.57 ± 1.18) participated in this study. All participants have no history of neurological or psychiatric disorders, and they were given the full instructions of the study and agreed to participate in the experiment. The experiment was conducted with the IRB (DGIST-170721-HR-025-08) approval of DGIST (Daegu Gyeongbuk Institute of Science and Technology).

B. Experimental Protocol

The experiment was conducted over two days. The subjects were asked to sit on a clinically used torso fixation chair with placing their right arm on the armrest of the chair in all sessions (Fig. 1(a)). On day 1, the motor execution and

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motor imagery task were performed to extract training data for implementing MI-BCI. On day 2, three different motor learning methods (MI-BCI, PT, and AT) were performed sequentially. Note that we used real time ERD detection using cross correlation and false positive rejecting method with two-phase algorithm [13] for the experiment.

Fig. 1(b) illustrates the experimental paradigms for the day 1 session. When auditory cue beeped, the subjects were asked to immediately perform motor execution or motor imagery of hand extension and flexion for one time. The auditory cue was repeated for 30 times with 12 seconds interval. Note that the motor execution task precedes the motor imagery task to make subjects be accustomed to the imagination of hand extension/flexion.

Based on training data of day 1, MI-BCI of day 2 was conducted. Fig. 1(c) illustrates the experimental paradigms for all day 2 session. Each session was repeated for 30 times with 12 seconds interval. After the baseline period (Fig. 1b), a green-light will appear for 2 seconds during each task to clearly distinguish between rest periods and the periods in which subjects concentrate on their motor imagery. In MI-BCI sessions, the subjects were asked to perform motor imagery similar to day 1, and neurofeedback was provided after detection if it occurs within 2 seconds after the cue. For PT sessions, the robot provides movement every time whenever the sound cue occurs. Here, the subjects were asked to relax without any thinking. After that, AT sessions was followed, and the subjects were asked to perform the same hand extension/flexion task themselves.

C. Data Acquisition

EEG data were recorded with sintered Ag/AgCl electrodes and ActiveTwo system (Biosemi, Netherlands). 32-channel

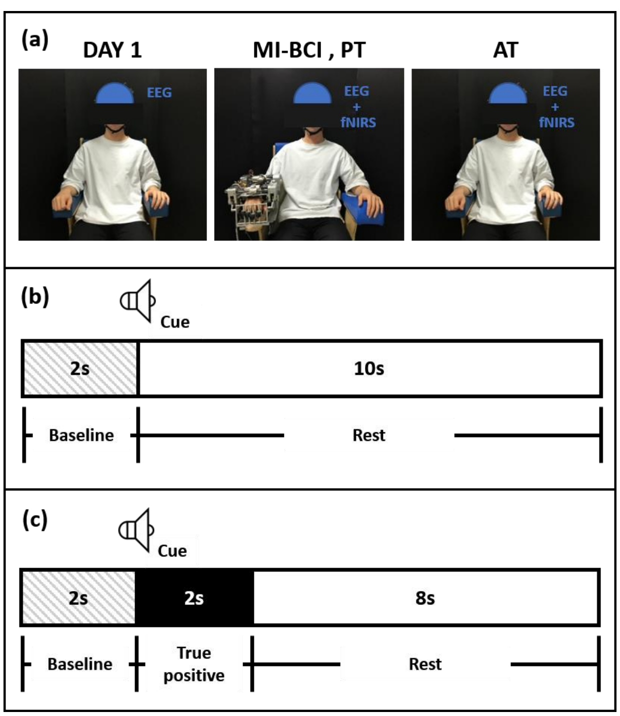

Figure 1. Experiment information (a) experimental setup (b) experimental paradigm of day 1. (c) experimental paradigm of day 2.

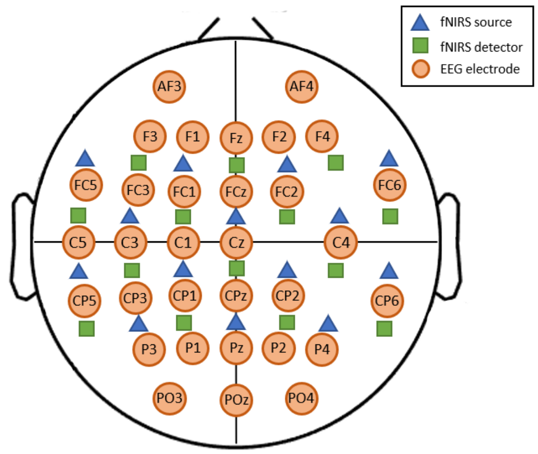

Figure 2. Location of electrodes and fNIRS optodes

electrodes were placed on the scalp according to the international 10-20 system, as shown in Fig. 2. fNIRS data were acquired simultaneously with EEG by LABNIRS (Shimadzu, Japan). A data acquisition device transmitted the digital trigger signal from fNIRS device to EEG device whenever the sound cue occurs. The used optode probeset consisted of 14 sources and 14 detectors embedded in the EEG electrode cap (Fig. 2). The distance between neighboring source and detector is approximately 3 cm, with each neighboring source-detector pair forming a channel [14], resulting in 45 channels in total.

D. EEG Data Analysis

EEG signals were collected at 128Hz sampling frequency. Raw data were re-referenced by the common average reference to attenuate noise [15]. Then we extract data epochs based on time information of the cue in the reference data, to generate a mean time-frequency map.

The mean event-related power changes in a time-frequency map could be visualized by the event-related spectral perturbation (ERSP), which provides detailed information on event-related desynchronization (ERD)/ event-related synchronization (ERS) patterns for different tasks. An ERSP of n trials was calculated according to the equation defined as follows:

$$ERSP(f,t) = \frac{1}{n}\sum_{k=1}^{n}(F_k(f,t)^2) \tag{1}$$

where $F_k(f,t)$ indicates the spectral estimation at frequency f and time t for the kth trial. The ERSP (dB) was computed using EEGLAB toolbox [16]. For the baseline-normalized ERSP, the mean power changes in a baseline period (2 s before task trial) were subtracted from each spectral estimation. In this study, the ERSP of C3, corresponding to hand motor tasks, was displayed from -2 to 4 s between 4 and 30 Hz, referring to the computing method of baseline-normalized ERSP.

For investigating topographic distribution, averaged ERSP of mu band (8-13 Hz), which was desynchronized when a motor task was performed [17], was calculated in each channel for task period.

E. fNIRS Data Analysis

In analyzing fNIRS data, we majorly used oxygenated hemoglobin (oxyHb) data, which is known to be sensitive to task-related changes [18]. NIRS_SPM (KAIST, Korea), a MATLAB-based software package for statistical analysis of fNIRS, was used [19] for the analysis. Gaussian smoothing with a full width at half maximum of 2 s and wavelet-MDL-based detrending were applied to compensate noise [20] and motion artifacts due to the subject's movement [21]. Pre-processed data were normalized and averaged for estimating the cortical hemodynamic response.

Averaged oxyHb response of C3, corresponding to hand motor tasks, was calculated in reactive time (6-8 s after the cue) and t-test was performed for statistical analysis. For investigating topographic distribution, averaged oxyHb and deoxyHb of each channel were calculated in reactive time.

III. Results

A. Event-Related Spectral Perturbation (ERSP)

Fig. 3(a) shows the averaged time-frequency maps across all participants for PT, MI-BCI and AT task conditions at C3. The ERSP maps present ERD patterns from task onset for all conditions. This represents that all the sessions performed well, and three different motor learning methods showed strong ERD patterns in a similar frequency band (10-15 Hz).

From topographic distribution results, as illustrated in Fig. 3(b), AT and MI-BCI showed the strongest activation observed near C3, whereas PT showed wider and weaker activation compared to the other two motor learning methods.

B. Hemodynamic response of the fNIRS

Fig. 4(a) shows the averaged oxyHb responses of C3 for

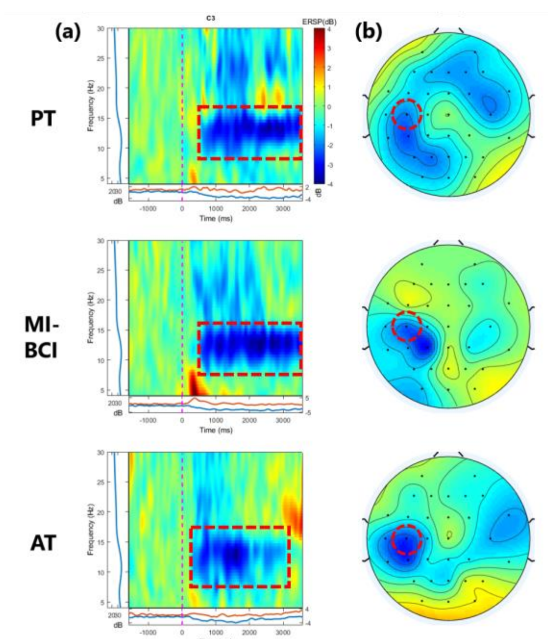

Figure 3. Averaged ERSP maps and topographic distribution. (a) ERSP maps of each task. Pink dot lines indicate the onset of the task. (b) Topographic distribution of averaged ERSP in each channel. Red dot circles indicate C3 channels.

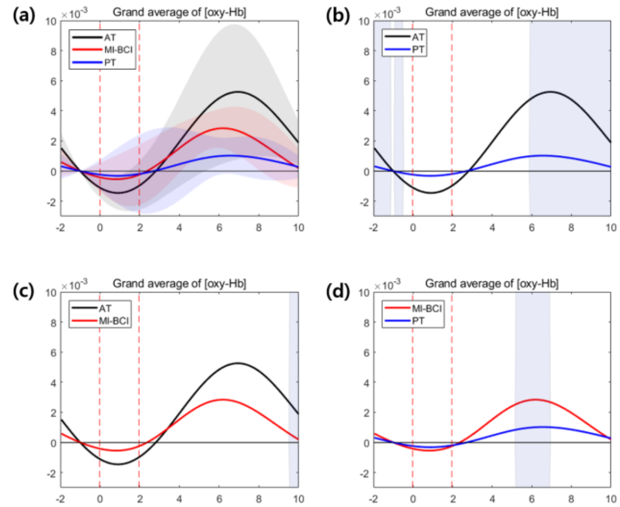

Figure 4. Hemodynamic responses (a) Averaged oxyHb response of C3 for three motor learning methods. (b)-(d) comparison of oxyHb responses of two motor learning methods.

three different motor learning methods. The shaded areas illustrate the standard deviation of each task, and red dot lines indicate the onset time of task and rest period. Fig. 4(b)-(d) represent comparisons of oxyHb responses of motor learning methods. The shaded areas indicate statistically significant time sample ($p<0.05$). Near the peak time (around 6 seconds), both AT and MI-BCI shows significantly stronger oxyHb response than PT (Figs. 4b and 4d), whereas there is no noticeable difference appeared between AT and MI-BCI (Fig. 4c).

Averaged oxyHb response of AT for reactive time is significantly higher than that of PT ($p=0.031<0.05$), and averaged oxyHb response of MI-BCI for reactive time almost reached significantly higher activation than that of PT ($p=0.055<0.6$). However, no statistical significance appeared between AT and MI-BCI ($p=0.170>0.05$) (Fig. 5).

Topographic distribution of averaged oxyHb, as illustrated in Fig. 6, shows that the entire cortical activation including C3 is higher both AT and MI-BCI, compared to PT (Fig. 6).

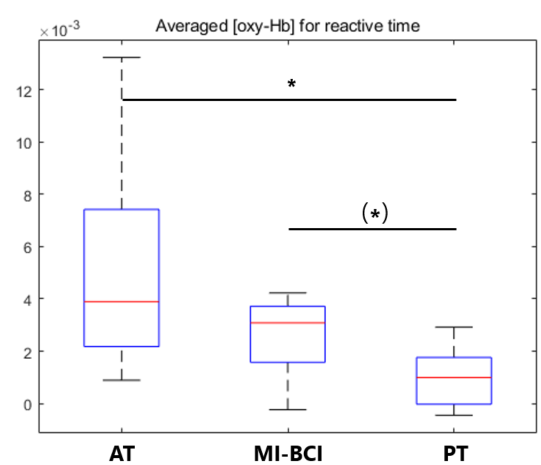

Figure 5. Boxplot of averaged oxyHb responses for a reactive time (6-8 seconds after cue). (*$p<0.05$, (*)$p<0.056$)

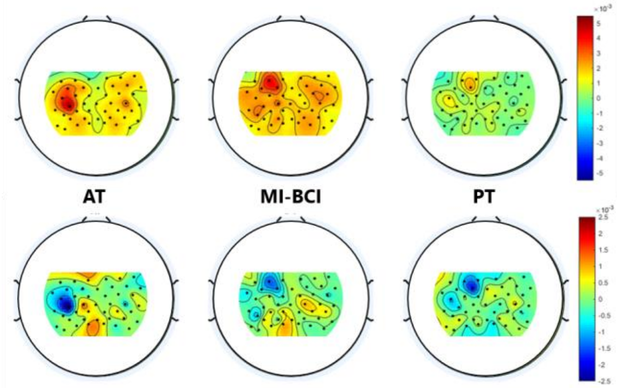

Figure 6. fNIRS topographic distribution for reactive time. Averaged oxyHb (upper row) and deoxyHb (lower row) responses for reactive time (6-8 sec after cue)

IV. Discussion

This paper aims to show feasibility that event-related design can be applicable for analyzing cortical effects of MI-BCI using fNIRS and EEG simultaneously. Moreover, the hemodynamic response functions of three different motor learning were obtained and compared by using the event-related design.

The hemodynamic results which come from fNIRS demonstrate that MI-BCI is more similar to AT than PT in cortical level, and both AT and MI-BCI induce much stronger activation than PT. These results conform the results from EEG and other existing studies which compared several different motor learning [7-10]. Therefore, this paper 1) also supports that MI-BCI will be able to provide more effective motor learning for the patients who cannot apply AT and 2) shows that event-related paradigm can be used to analyze cortical effects of MI-BCI and comparison of different motor learning methods.

It is noteworthy that AT showed the shortest desynchronization time in the averaged ERSP map (Fig. 3a). It was because MI-BCI and PT were implemented by hand robot (Fig. 1a), which has longer execution time than AT (the subjects' motor execution).

Based on the finding on the feasibility of the event-related design, we will attempt to analyze the cortical effects of MI-BCI with true positive (feedback due to motor imagery) and false positive (feedback without motor imagery) cases separately [13], as future works. In addition, further studies with larger population might be needed to investigate what the factors are to determine the individual differences of brain activation with motor learning methods.

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