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LETTER

Detecting Motor Learning-Related fNIRS Activity by Applying Removal of Systemic Interferences

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SUMMARY Functional near-infrared spectroscopy (fNIRS) is a non-invasive neuroimaging technique, suitable for measurement during motor learning. However, effects of contamination by systemic artifacts derived from the scalp layer on learning-related fNIRS signals remain unclear. Here we used fNIRS to measure activity of sensorimotor regions while participants performed a visuomotor task. The comparison of results using a general linear model with and without systemic artifact removal shows that systemic artifact removal can improve detection of learning-related activity in sensorimotor regions, suggesting the importance of removal of systemic artifacts on learning-related cerebral activity.

key words: *fNIRS, brain, motor learning, scalp artifact reduction*

1. Introduction

Functional near-infrared spectroscopy (fNIRS) is a non-invasive neuroimaging technique, which measures relative changes of oxygenated and deoxygenated hemoglobin concentration (ΔOxy-Hb and ΔDeoxy-Hb) [1], [2]. fNIRS has several advantages including minimal constraint, resistance to electrical artifacts, and portability. For these reasons, fNIRS has been used for evaluation during motor learning in many studies [3]–[8].

Recently, several studies have revealed that fNIRS signals are contaminated with a systemic artifact, which may originate from changes in blood pressure or heart rate [2]. Such artifact is unavoidable since these changes occur on the surface (scalp) layer or even in the cortical layer, through which near-infrared light passes. Therefore, proper removal of scalp hemodynamic artifacts is critical for estimating true brain activity using fNIRS analysis [2], [9]. However, the effects of these artifacts during motor learning tasks have not been thoroughly investigated.

Here we examined whether systemic (scalp) artifact removal can improve detection of motor learning-related fNIRS activity. We considered two hypotheses on the effects of scalp artifacts during learning tasks. In general, learning-related cerebral activity is evaluated by changes between early and late phases of the learning. Thus, the first hypothesis proposes that if scalp hemodynamic artifacts constantly contaminate fNIRS signals across learning, no influences of the scalp artifacts on learning-related cerebral activity would be expected because the artifacts would be canceled out. In this case, one can identify the learning-related cerebral activity without any scalp artifact removal methods. On the other hand, the second hypothesis proposes that if systemic changes reflected in scalp hemodynamics can be modulated by cognitive load or task difficulties, the scalp hemodynamics would obscure actual cerebral activity, potentially producing false positive or negative results. If this holds true, scalp artifact removal is necessary for accurate evaluation of learning-related cerebral activity.

To examine if scalp artifact removal is required for the detection of learning-related cerebral activity (i.e., which hypothesis is true), we measured brain activity by fNIRS while subjects performed a visuomotor tracking task [10]. As a scalp artifact removal method, we applied a method using short probe distance channels, which is proven to be effective for motor tasks in the previous study [9] and identified learning-related brain activity using a general linear model (GLM) with or without scalp hemodynamic artifact removal. By comparing the results with and without scalp artifact removal, we investigated if the detection of cerebral activity associated with motor learning is improved by the removal of scalp artifacts.

2. Materials and Methods

2.1 Experimental Procedures

The experiment was designed according to principles of the Declaration of Helsinki and was approved by the ethics committee of Nagaoka University of Technology. Nine healthy right-handed men (age: 23 ±1.4 years; range: 21–25 years) participated in the experiment. Before the experiment, each subject received instructions and signed an informed consent form.

Each subject sat in a chair and performed the task while looking at a display positioned in front of him (Fig. 1A). The height of the desk was set to the optimum height for each subject. A touch panel (ET2200L, Elo Touch Solutions, Kanagawa, Japan) was installed so that it was parallel to the desk and monitor. Subjects wore gloves to avoid the effects of friction.

The experiment was conducted in two days, which consisted of six sessions in one day, with each session including five trials. A trial consisted of 10-s pre-tracking, 20-s rotation-tracking, and 20-s post-tracking. The task was to

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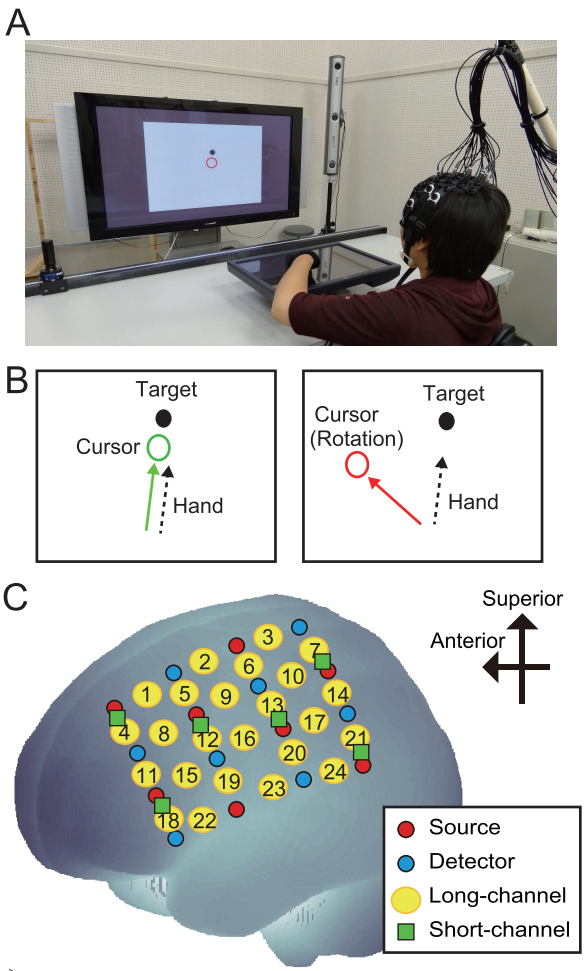

Fig. 1 Experimental setting (A), task setting without (left) and with (right) rotational transformation (B), and fNIRS probe location (C). Twenty-four Long-channels and 6 Short-channels were measured.

track a circle target with a cursor related to subject hand position. During the rotation-tracking, the subject performed the task with rotational transformations (60°) of the cursor (colored in red), where the cursor movement is rotated with 60° in the counterclockwise direction relative to the hand position (Fig. 1B, right), while they tracked the target without any transformations of the cursor (colored in green) during pre- and post-tracking (Fig. 1B, left). A brief rest lasting about one minute was given after each trial, and a 3-minute break was given after each session. The cursor and the target movement were sampled every 20 ms (sampling frequency: 50 Hz). We used the fNIRS system (FOIRE-3000, Shimadzu Corp., Kyoto, Japan), which consisted of 24 standard 30-mm probe (light source and detector) distance channels (Long-channels) and 6 shorter probe distance channels (Short-channels; 15 mm). Because all subjects used their right arms, we measured brain activity in the left hemisphere. Each probe was placed over the left sensorimotor cortex centered at C3 of the international 10-20 system (Fig. 1C). Raw fNIRS data (attenuation of the light intensity) were sampled every 130 ms. After measurement, each probe position was recorded with a stylus marker (FASTRAK, Polhemus, Colchester, VT, USA).

2.2 Behavioral Analysis

To evaluate behavioral performance of tracking, we calculated tracking errors, which were averaged Euclidean distances between the cursor and the target during the rotation-tracking. The error value was normalized by dividing the same distances during post-tracking and was calculated for each trial in each subject and then averaged across subjects.

2.3 fNIRS Analysis

Pre-processing for fNIRS data was done in accordance with the following procedure. First, raw fNIRS data for each detector were converted into hemoglobin concentration data (ΔOxy-Hb and ΔDeoxy-Hb) using modified Beer-Lambert Law [11]. Next, the fNIRS hemoglobin data were normalized (z-scored) by subtracting a mean value over an interval from 0 to 5 s before the start of rotation-tracking (referred to as baseline) and dividing by the standard deviation of baseline. Finally, temporal smoothing was performed using a moving average with a window size of 2 s.

To compare the effects of scalp artifact removal when identifying task-related cerebral activity we performed GLM analysis with and without scalp artifact removal. In cases applying the removal we used a method to incorporate scalp hemodynamic components into the model, referred to as ShortPCA [9]. In this method, the equation used for the analysis of fNIRS Long-channel in each trial is as follows:

$$\boldsymbol{Y_i} = \beta_{c,i}\boldsymbol{X_c} + \beta_{s,i}\boldsymbol{X_s} + \boldsymbol{C_i} + \boldsymbol{\varepsilon_i}, \tag{1}$$

where i is an index of fNIRS channel, $\boldsymbol{Y_i}$ is preprocessed fNIRS hemoglobin data for the channel i ($1 \times T$ vector; T is number of samples in a trial), and $\boldsymbol{X_c}$ is a component ($1 \times T$) relating to cerebral activity during the rotation task. This was created by convoluting a 20-s boxcar function representing the rotation task with the canonical hemodynamic response function [12]. $\boldsymbol{X_s}$ is a component ($1 \times T$) to model scalp hemodynamic artifacts and was estimated using principal component analysis (PCA) applied to Short-channel signals [9]. To remove the global scalp hemodynamic artifacts, which are distributed across channels, we considered three principal components as scalp hemodynamic artifacts because these could represent the majority of the Short-channels (explained more than 90% of variance). $\boldsymbol{C_i}$ is a constant vector ($1 \times T$) for the channel i, and $\boldsymbol{\varepsilon_i}$ is an error term for the channel i. Using this model, we conducted first-level analysis, where estimated weights for cerebral and scalp hemodynamics, $\beta_{c,i}$ and $\beta_{s,i}$, were determined using the ordinary least square method for each channel i and each trial in each subject. Then, learning-related cerebral activity was evaluated as the differences of averaged beta values between early and late phases of learning (i.e., increased activity in the early phase compared with that in

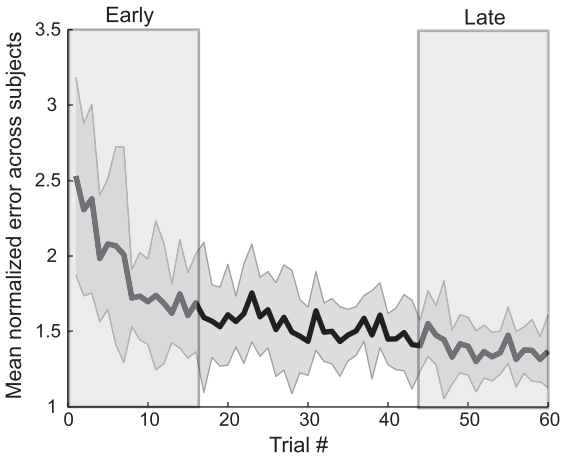

Fig. 2 Changes in averaged tracking errors (bold line) during learning. Dark gray shade area indicates standard error across subjects. Trials 1–15 and 46–60 are defined as early and late phase of the learning, respectively.

the late phase). We set trials 1–15 as early phase and trials 46–60 as late phase. We then conducted a group-level analysis to find the brain regions exhibiting learning-related cerebral activity. A one-sample t-test was used to test statistical significance of the learning-related change for each channel. Calculated t-values were mapped onto the subject-averaged channel positions using the NFRI function toolbox [13]. In addition to analysis with ShortPCA, we performed GLM analysis without scalp artifact removal using a standard GLM (Standard), i.e., without scalp hemodynamic components ($\beta_{s,i}\boldsymbol{X}_s$ in Eq. (1)). To examine the effects of removing scalp hemodynamics, the results with Standard and ShortPCA were compared.

3. Results

3.1 Behavioral Results

Figure 2 shows the averaged tracking error across subjects. We found that the tracking error was reduced with practice. A large decrease in errors was observed in the early phase of learning (trials 1–15). After the early phase, changes in errors were relatively small and reached plateau in the late phase of learning (trials 46–60). Thus, subjects learned the rotation transformation through repetition, and learning-related changes of brain activity can be detected by comparison of the fNIRS signals between early and late phases.

3.2 Comparison of Learning-Related Brain Activities

Although we observed learning-related cerebral activities for both GLM analyses (Standard and ShortPCA) in ΔOxy-Hb, their patterns were not the same (Fig. 3). In ΔOxy-Hb, a wide range of learning-related activity was found at the measurement channels without scalp artifact removal (Standard, Fig. 3A, left), while detected learning-related activity using ShortPCA was located on anterior and posterior parts of the channels, corresponding to the prefrontal cortex

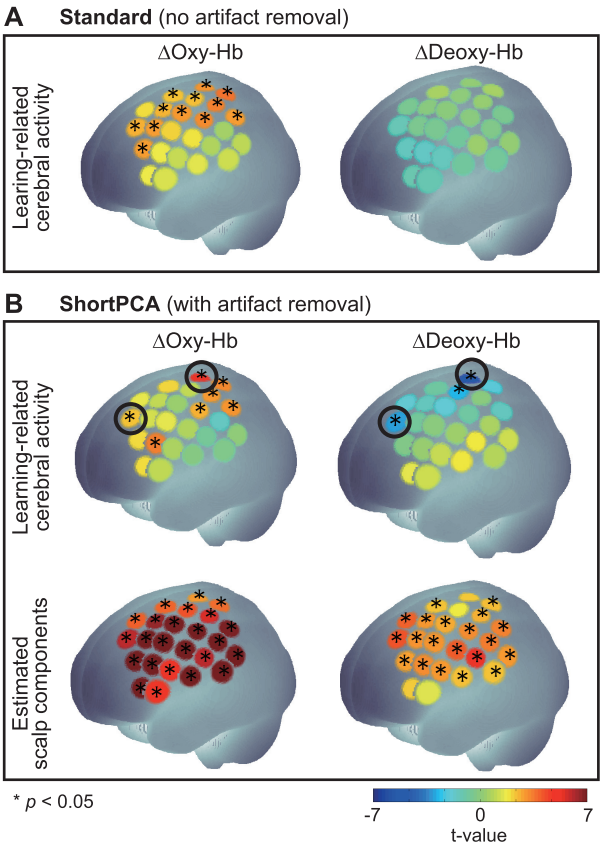

Fig. 3 Group-level results for ΔOxy-Hb (left) and ΔDeoxy-Hb (right). (A) learning-related cerebral activity (t-value) obtained by the standard model. (B) learning-related cerebral activity (upper) and estimated scalp components (lower) for ShortPCA. Asterisks show significant difference in activity ($p < 0.05$). Black circles indicate the channels showing significant changes for both ΔOxy-Hb and ΔDeoxy-Hb. The t-values were mapped onto the cortical surface using [13].

and primary sensorimotor area, respectively (Fig. 3B, upper left). Results for ΔDeoxy-Hb were more distinct between analyses. We observed significant learning-related changes (decreases) only for ShortPCA (Fig. 3B, upper right). Importantly, we found significant differences in the learning-related changes for both ΔOxy-Hb and ΔDeoxy-Hb in two channels (channels 3 and 4, black circles in Fig. 3B, upper panel). In addition, in ShortPCA, components of scalp artifacts were estimated over all measured channels (Fig. 3B, lower panel).

4. Discussion

In the present study, we investigated whether scalp artifacts influence detection of learning-related fNIRS activity. We are of the opinion that our GLM analysis with artifact removal was able to accurately detect changes in cerebral activity related to motor learning for the following reasons. First, using removal of artifacts, the learning-related changes were more localized in the sensorimotor and prefrontal cortices in ΔOxy-Hb and were detected in ΔDeoxy-Hb. This is consistent with a previous study, in

which learning-related changes were generally found in prefrontal and sensorimotor cortices as well as in parietal cortex and cerebellum [10], [14]. Second, we found a learning-related decrease of ΔOxy-Hb and increase in ΔDeoxy-Hb for two measured channels. This inverse relationship between two hemoglobin types is a typical pattern that reflects actual cerebral hemodynamic changes in fNIRS, whereas the increase in just ΔOxy-Hb or in both hemoglobin types is thought to reflect false positive activity due to scalp artifacts [1], [2]. Thus, our results showed a reasonable spatial pattern of activity and hemoglobin profiles, supporting effective removal of the scalp artifact by our method.

Because of the advantages of fNIRS, as described above, many previous studies have conducted motor learning experiments with fNIRS measurement and have reported learning-related cerebral activity in sensorimotor and prefrontal cortices [3]–[8]. However, few studies have considered the influences of scalp artifacts [8]. To our knowledge, this is the first study to examine such influences on the broad measurement of motor learning activity using multiple channels. Our results are consistent with the hypothesis that scalp artifacts are modulated by cognitive load or task difficulties [2] rather than constantly contaminating measured signals. Thus, removing such artifacts may increase detectability of learning-related activity.

It should be noted that performing a group-level analysis of a large sample size of subjects could attenuate the effects of scalp artifacts due to variability. This could explain why some previous studies have detected a localized learning-related activity pattern without using artifact removal (e.g. [3], [4]). Further investigation is required to confirm this hypothesis because of our limited sample size (n=9).

Here we showed that our method using just a few short distance probe channels (Short-channels) [9] can be used for scalp artifact removal during motor learning tasks. Nevertheless, several different artifact removal methods have been proposed so far [2]. Future studies are needed to examine whether these other methods can be used in the context of motor learning and to determine if more effective methods exist.

Acknowledgments

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