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A NIRS-based Brain-Computer Interface System during Motor Imagery: System Development and Online Feedback Training

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Abstract— **A brain-computer interface (BCI) to detect motor imagery from cerebrum hemodynamic data measured by NIRS (near-infrared spectroscopy) was constructed and the effect of the online feedback training for subjects was evaluated. Concentrations of Oxy- and deOxy-hemoglobin in the motor cortex during motor imagery of subject's right hand was measured by 52-channel NIRS system, and the mean magnitude of measured signal near C3 in the International 10-20 System was visually fed back online to the subject. On two out of three subjects, it was shown that the ratio between the averaged value and the standard deviation over trials (S/N ratio) of Oxy-hemoglobin signal elicited by the imagery of subject's right hand was increased by the 5-day online feedback training. Detailed investigation of the effect of the online feedback training on brain activities was left for further study.**

I. INTRODUCTION

For the better communication of severe paralyzed patients due to stroke, spinal cord injury or motor neuron diseases like ALS (amyotrophic lateral sclerosis), the Brain-Computer Interface (BCI) has attracted interest [1]. On the BCI system, brain activities were measured noninvasively by EEG (electroencephalogram) or NIRS (near-infrared spectroscopy), and the measured signals were analyzed to extract and detect user's intensions or "thoughts".

On the EEG-based BCI to detect motor imagery, the increase (event-related synchronization: ERS) or decrease (event-related desynchronization: ERD) of EEG band power on μ or β frequency range is generally observed when the subject imagines movement of his/her own limb, and such features have been used for command detection [2], [3]. But the low S/N ratio and poor reproducibility of EEG elicited by motor imagery have hindered improving accuracy of detection.

Pfurtscheller et al. and the authors have proposed the "Brain Switch" BCI system to detect a motor imagery from one channel of EEG, on which the power increase (ERS) of EEG β oscillation due to motor imagery is detected on threshold-basis [4], [5]. This system enables binary switching only by using one channel of EEG. And the authors have also reported that training was effective to improve the accuracy and reproducibility on this system [5].

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Then, the authors investigated the effect of online feedback training to improve S/N ratio of band power at the "target" frequency band in the Brain Switch system [6]. In this study, EEG band power of interest for command detection was visually fed back to the subjects, and they were asked to increase the band power during motor imagery. It was shown that the online feedback training improved the S/N ratio and reproducibility of the target frequency component in EEG, but if the features for feedback information (frequency band, electrode location or montage) were not selected correctly, such a training would cause negative effects. Especially, to specify the appropriate range and the central frequency of EEG is important, because several narrow-range frequency components of EEG which were related to motor imagery were embedded in the range of about 8 to 35 Hz and the central frequencies were not fixed during the online feedback training process [6].

In this study, we focused on a BCI system to detect motor imagery of the user's limb using NIRS measures. NIRS is a measure of the metabolic rates of Oxy- and deOxy-hemoglobin (Oxy-Hb, deOxy-Hb) which are elicited by the regional activation of the brain. Rich spatial resolution of NIRS is suitable to determine the limb of motor imagery, because the execution or imagery of the limb movement is represented as a localized activation in the sensorimotor area.

And, due to the slow change of hemodynamic levels, frequency range of NIRS signals elicited by the brain activation is narrow. Various profiles of electric activity of neuronal network (e.g. change of rate and synchrony of neuronal firing) are represented by the slow increase or decrease of hemodynamic concentration. Therefore, on the feedback training for BCI based on motor imagery, NIRS measurement has advantages that the precise parameter setting to extract features is not needed to detect information on the brain activity and that such information is straightforward for users to interpret as a feedback of brain activity.

In this article, the effect of online feedback training on the BCI system to detect motor imagery from NIRS signals measured at the sensorimotor area is reported. NIRS-based BCI systems to detect motor imagery have been tested by Coyle et al. [7] and Sitaram et al. [8], but in these studies, online feedback training by using NIRS signals has not been executed.

II. METHODS

A. Online Feedback Training System for NIRS-based BCI

The online feedback training system for NIRS-based BCI was developed. This system consisted of the NIRS

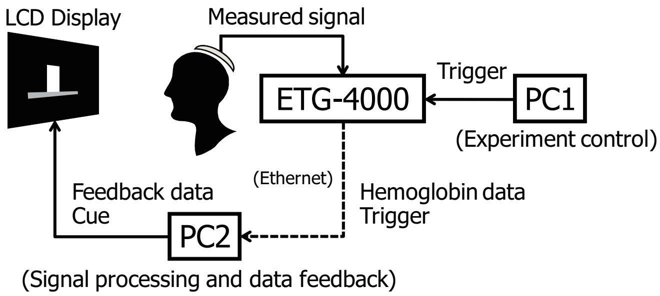


Fig. 1. Online feedback training system for NIRS-based BCI

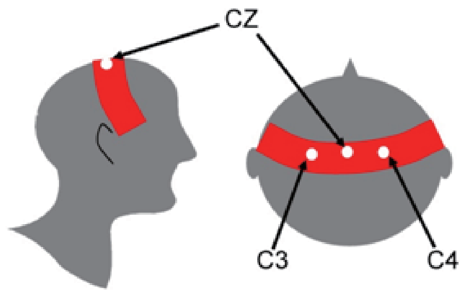


Fig. 2. Setting of probes for NIRS measurement

measurement system (ETG-4000, Hitachi Medical Corporation, Japan) and two laptop PCs (Fig. 1). PC1 generated triggers which indicated the onset and offset of the tasks which subjects were instructed to do, and sent them to the NIRS measurement system via a serial connection port. The NIRS measurement system measured 52-channel Oxy-Hb and deOxy-Hb levels at the sampling frequency of 10 Hz. These data were acquired and were transported to PC2 via Ethernet. On PC2, the feedback data was calculated from the data received from the NIRS measurement system, and was presented together with the timing of the tasks on LCD display of PC2. Both PCs worked on Windows XP Professional, and MATLAB is used for experimental control and analysis.

B. Calculation of Feedback Data $L(t)$

The feedback data $L(t)$, which was presented to the subject online during experiments, was calculated by the following way; three channels were chosen for each subject from the contralateral (left) hand area of right hand movement (near C3 in the International 10-20 System on EEG measurement). The Oxy-Hb data taken from these three channels were then averaged, and after applying a high-pass filter at 0.04 Hz (Chebyshev Type II) to reduce drifts, the data was smoothed by 7-point simple moving average.

C. Experiment

Three volunteers (ages 21$\sim$22) took part in the experiment as subjects. The experiments in our study were approved by the Ethics Committee on Clinical Investigation, Graduate School of Engineering, Tohoku University, and was performed in accordance with the policy of the Declaration of Helsinki. Subjects who sat in front of the LCD display connected to PC2 were requested to gaze at a short horizontal line (fixation line) shown on the display.

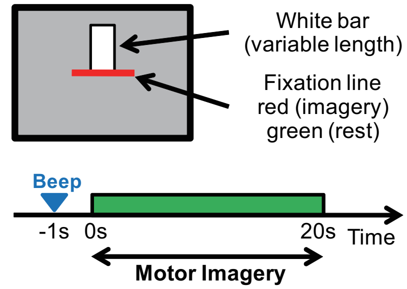


Fig. 3. Time chart of experimental paradigm

During experiments, 52-channel Oxy-/deOxy- hemoglobin concentration rates were measured. The wavelengths of the irradiation light were 780 and 830 nm. Thirty-three probes used to measure responses were arranged on a 3-by-11 probe holder. The center of the probe holder was near CZ as defined by the International 10-20 System, and the holder was set so as to cover the sensorimotor cortex. (Fig. 2)

The time chart of this experiment is shown in Fig. 3. The subject was instructed to imagine movement of his/her own right hand for 20 seconds from time 0. One second before starting the task, a beep tone was presented as a warning. The fixation line was colored green and turned red during imagery period. Additionally, a vertical white bar whose length was proportional to the feedback data $L(t)$ was displayed all the time. Bar length was updated on every 0.5s. Inter-stimulus interval was randomly varied from 40 to 43 s.

The subject was instructed to control the length of the presented white bar by the imagery of his/her right hand movement: as long as possible during imagery period, and as short as possible during resting state.

The online feedback training experiments were conducted for 5 days. Experiments on each day consisted of 6 sessions, each of which had 5 trials of motor imagery. Before and after the 5-day online feedback training experiments, the evaluation experiments of 3-class motor imagery (left, right and feet movement imagery) without feedback were executed for evaluating the effect of the online feedback training. (The results on left hand and feet movement imagery were not used for the present study.)

III. Results and Discussion

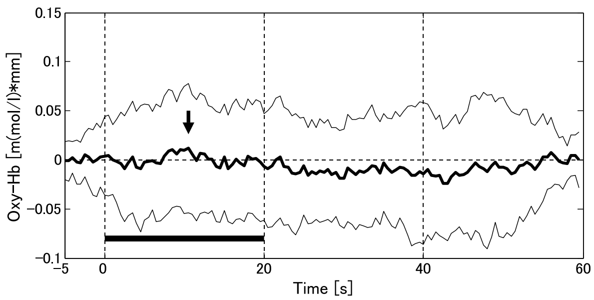
The responses to motor imagery were determined, and the effect of the online feedback training on the activation in the sensorimotor cortex was investigated. The signal-to-noise ratio and the spatial distribution of measured Oxy-Hb signals were evaluated.

A. Changes of Feedback Data $L(t)$

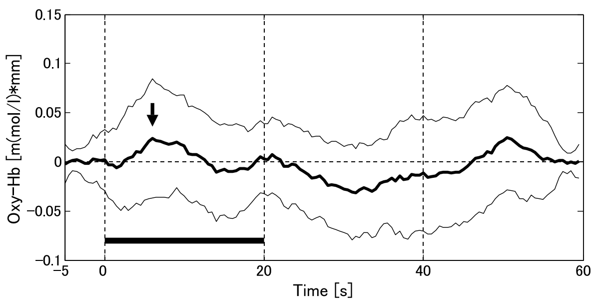
The change of the feedback data $L(t)$, presented to the subject during the online feedback training as a length of a white bar, was investigated.

Although high-pass filter was applied to the original signal which was averaged over selected 3-channel data, $L(t)$ still

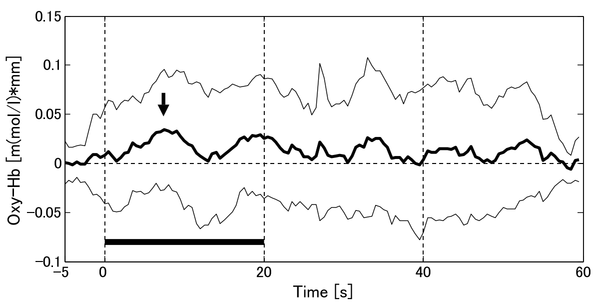
(a) Day 1



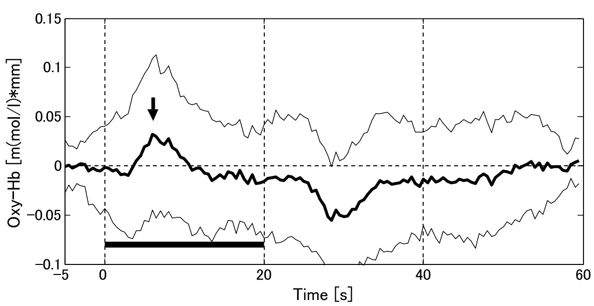
(b) Day 2



(c) Day 3



(d) Day 4



(e) Day 5

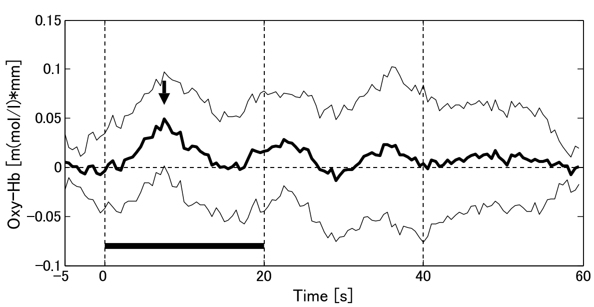
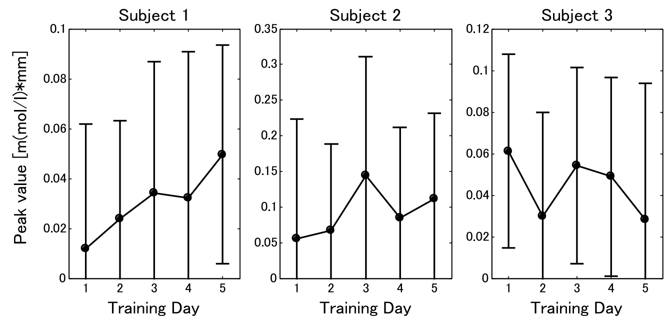


Fig. 4. Example of averaged responses (thick lines) and their standard deviation (thin lines) on each training day (Subject 1). Black bars denote the period of motor imagery.

(a) Peak value



(b) S/N ratio

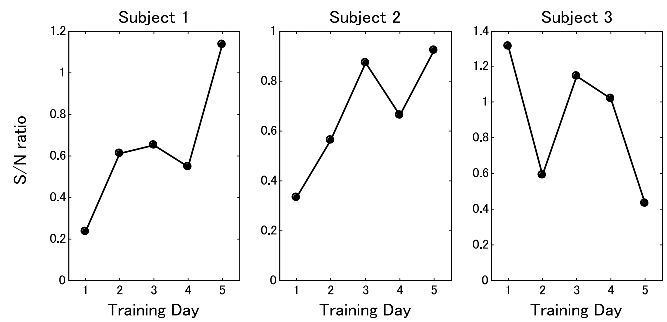


Fig. 5. Averaged Oxy-Hb concentration value at peak latency during motor imagery. (a) Peak value and standard deviation, (b) S/N ratio.

contained certain low frequency variations due to drifts. But the changes elicited by motor imagery were observed in $L(t)$, and it was reported by the interviews after the experiments that all the subjects recognized such changes during the experiments. It is expected, therefore, that the overall information on the change of Oxy-Hb concentration was actually fed back to the subjects during the online feedback training.

B. Changes of $L(t)$ Averaged Over Trials

To evaluate the effect of the online feedback training on the target Oxy-Hb value, $L(t)$ was averaged over trials and was evaluated with its standard deviation.

The averaged value $V(t)$ was calculated by the following; $L(t)$ on each trial was extracted from -5 to 60 s from onset of the motor imagery task, and the trend due to drift was removed by linear approximation, by using the averaged values of the data at -5 to -3 s and 58 to 60 s.

$V(t)$ and its standard deviation over trials on each day in the online feedback training experiments to Subject 1 is shown in Fig. 4. It can be found that, on this subject, the peak value during motor imagery was increased as the training went on. On the other hand, the variation of standard deviation on training day was small.

Next, the change of the peak value of Oxy-Hb concentration and its standard deviation during 5-day online feedback training was evaluated. The peak Oxy-Hb concentration value and its standard deviation over trials, and the S/N ratio (defined by the peak value divided by the standard deviation at the same latency) on all subjects are shown in

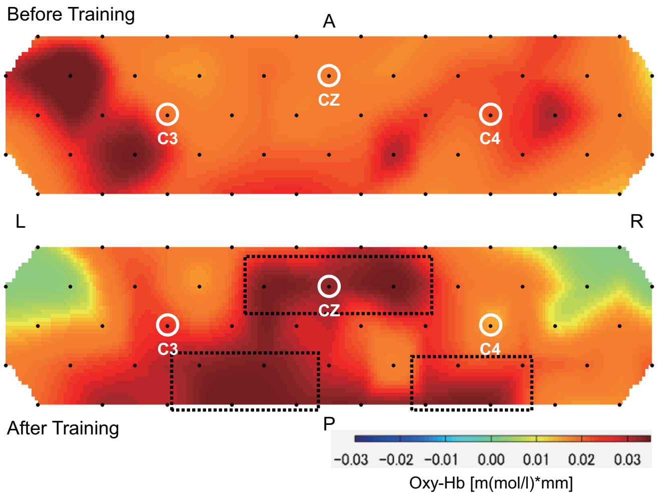


Fig. 6. Example of the spatial distribution of Oxy-Hb concentration at peak latency during motor imagery.

Fig. 5. It was shown that the positive peak value of $V(t)$ increased by training on Subjects 1 and 2, and that the standard deviation at the peak latency was not changed by training on all subjects (Fig. 5(a)). Then on these subjects, the S/N ratio increased during the 5-day training sessions (Fig. 5(b)). These results mean that the magnitude of cortical activation elicited by motor imagery and its reproducibility were improved by the online feedback training. It will help the improvement of the accuracy of the BCI based on motor imagery.

C. Change of Spatial Distribution of the Response

It is generally known that the specific contralateral site on the sensorimotor area is activated when the subjects execute or imagine body movement ("motor homunculus"). In case of the right hand, the change of activation of the hand area in the left hemisphere (near EEG location C3) is mainly observed by EEG, MEG, NIRS and fMRI. The object of such motor imagery can be determined from the spatial distribution of cortical activation.

Spatial distributions of Oxy-Hb concentration before and after the online feedback training were compared by the results of experiments without feedback which were executed before and after 5-day online feedback training. Fig. 6 shows an example of the spatial distribution of Oxy-Hb concentration at the latency of peak activation during motor imagery. Before starting the online feedback training, the Oxy-Hb activation was widely distributed to the whole area. But after completing 5-day online feedback training, large activation on the contralateral hand area (near the left hand area on the motor cortex, anterior to C3), small activation on the ipsilateral hand area (anterior to C4) and on the vertex area (near CZ) were observed. This result suggests that the spatial distribution of cortical hemodynamics became more localized by the online feedback training. On Subject 2, Oxy-Hb activation became larger on both contralateral and ipsilateral site, and on Subject 3, no characteristic activation was observed after 5-day online feedback training.

It has been shown that the activation of the motor cortex elicited by motor imagery is weaker than that by motor execution [9], and the functional relationships between motor cortex, SMA (supplementary motor area) and other related areas during motor execution/imagery have been discussed [10]. More detailed investigations using EEG/MEG or fMRI as well as NIRS are left for further studies.

IV. Conclusion

A BCI system that detects motor imagery by NIRS measurements with online feedback was constructed, and the result of the online feedback training was reported in this article. On two subjects out of three, it was shown that after 5-day online feedback training, magnitude and its S/N ratio of Oxy-Hb hemodynamics during motor imagery were improved, and the spatial localization of Oxy-Hb activations became more localized. Experiments to verify the present results with more subjects, and more precise investigations by using multimodal measurements (EEG/MEG, fMRI and NIRS) were left for further study.

V. ACKNOWLEDGMENTS

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