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# A Multimodal fNIRS and EEG-Based BCI Study on Motor Imagery and Passive Movement*

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*Abstract*—**In EEG-based motor imagery Brain-Computer interface (BCI), EEG data collected in the calibration phase is used as a subject-specific model to classify the EEG data in the evaluation phase. Previous study has shown the feasibility of calibrating EEG-based BCI from passive movement. This paper investigates the primary sensorimotor area activation from fNIRS on 4 subjects using multimodal NIRS and EEG-based BCI system while performing motor imagery and passive movement of the hand by a Haptic Knob robot. NIRS_SPM is used to compute the changes in hemoglobin response and to generate brain activation map based on the contrasts of motor imagery versus idle and passive movement versus idle. The results on the contrasts showed that passive movement versus idle yielded significant differences compared to motor imagery versus idle. In addition, the results of classifying the NIRS and EEG data separately also showed that the accuracies on classifying passive movement versus idle are better than that of motor imagery versus idle. The results suggest a potential of using passive movement data to calibrate motor imagery in a multimodal NIRS and EEG-based BCI.**

## I. Introduction

A brain computer interface (BCI) allows direct communication and control of external devices using brain signals [1]. The brain signals can be acquired by electroencephalogram (EEG), near infrared spectroscopy (NIRS) and other modalities like functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), positron emission tomography (PET) from a subject. EEG is widely used because of its good temporal resolution, easy portability and low cost of setup [2]. EEG-based motor imagery BCI is a promising technology which translates the imagination of movements into commands and has the prospects for neurological rehabilitation [3]. Generally the motor imagery BCI works in two phases, the calibration phase and the evaluation or feedback phase[4]. In the calibration phase, EEG data acquired from a subject while performing motor imagery is used to train a subject-specific model. In the evaluation phase, the subject-specific model is used to classify the EEG data and translate the output into control signals.

Since higher model accuracy provides a more refined control for a BCI system, many studies have attempted to propose effective methods to improve the accuracy level. Study [5] proposed a parse common spatial pattern algorithm for EEG channel selection to yield the best classification accuracy s. Study [6] came up with a Filter Bank Feature Combination (FBFC) approach using Common Spatial Pattern (CS) and Phase Lock Value (PLV), yielding a significant improvement in cross-validation accuracies. Study[7] presented an integrative clustering and support vector-based active learning method to increase the classification accuracy of motor imagery EEG signal. Study [8] investigated the feasibility of calibrating EEG-based motor imagery BCI from passive movement. This study showed that the calibration performed using passive movement yielded higher model accuracy than the calibration performed using motor imagery with no significant differences.

NIRS-based BCI is an emergent technology. As a non-invasive optical functional brain imaging technique, fNIRS measures the concentration changes of oxygenated hemoglobins (HbO) and deoxygenated hemoglobins (HbR) in the superficial layers of the human cortex by means of distinct absorption spectra in the near-infrared range [9] . fNIRS is safe, portable and has high spatial resolution. This high spatial resolution property makes NIRS as a suitable technology to determine the motor imagery of hand as imagery of the hand movement is represented as a localized activation in the primary sensorimotor area. The feasibility of using NIRS-based motor imagery BCI has been demonstrated in studies. Study [10] tried to detect motor imagery with online feedback in a NIRS-base motor imagery BCI system. Study [11] introduced a multimodal NIRS and EEG-based system and used NIRS as a predictor for EEG-based BCI performance. To the best of our knowledge, there is no result of multimodal BCI study focusing on passive movement in previous literatures.

Motivated by the study in [8], this paper investigates the motor area activations from subjects performing motor imagery and passive movement using a multimodal NIRS and EEG-based BCI system. Simultaneous recordings of NIRS and EEG are collected from 4 healthy subjects performing motor imagery or passive movement. NIRS_SPM [12] is used to generate the brain activation map based on the two contrasts defined as motor imagery (MI) versus idle (MI vs Idle) and passive movement (PM) versus idle (PM vs Idle). In addition, this study classifies the NIRS and EEG data separately using the method in study [13] and study [8] respectively.

The remainder of this paper is organized as follows: Section II describes the subjects, the simultaneous NIRS and EEG data collection, experimental protocol and data processing and analysis. Section III presents the experimental results. Section IV concludes the paper.

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## II. Subjects and Method

### A. Subjects

4 healthy subjects from staffs and students from the Brain-Computer Interface laboratory in the Institute for Infocomm Research, A*STAR participated in this study. Ethics approval was obtained. All subjects were fully informed, and signed the consent form. All subjects were asked to use their right hand in the experiment.

### B. Data acquisition

In this study, NIRS and EEG data were collected simultaneously. The continuous wave NIRS instrument NIRx DYnamic Near-Infrared Optical Tomography (DYNOT) Imaging System (NIRx Medical Technologies, LLC.) recorded fNIRS data using two wavelengths ($\lambda$ = 760 & 830 nm) with a sampling rate of 1.81 Hz, with 64 optical fibers (32 sources and 32 detectors respectively). EEG data were recorded with a multichannel EEG amplifier (ANT by ANT Neuro, a Dutch corporation) equipped with 32 Ag/AGCl electrodes plus GND, 4 bipolar - EMG, EOG, EKG and 4 auxiliary input for GSR, nasal flow, pH sensor, temperature; sampling rate at 256.

WaveGuard EEG Cap, product of eemagine Medical Imaging Solutions GmbH, Berlin, Germany, was used for this study. NIRS optobes holders and EEG electrodes were integrated in a standard EEG cap (international 10-20 system). As the trajectory of the photon path from source to detector is assumed to be a ‘banana’ shape between the two optobes [14], the signal quality of two source/detector pairs is good only when the path length is within an effective range. Due to the constraint of space and size of the NIRS optobes holder, not all the distances of NIRS pairs of source and detector crossing over each EEG electrodes are within the effective distance. To get more effective channels, the NIRS optobes layout arrangement is to put as many optobes as possible to be around the EEG electrodes near the motor area of the subject’s head as shown in Fig. 1.

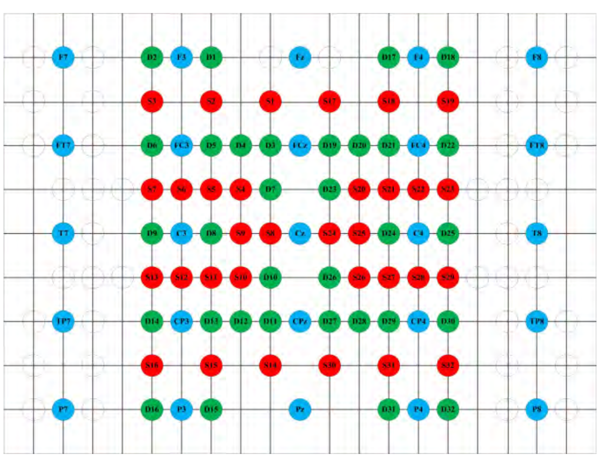

Figure 1. Optobes layout arrangement. The blue dots represtent EEG electodes, while red and green dots represent the NIRS optobes sources and dectors respectively.

Figure 2. The multi-modal NIRS+EEG experiment setup for subject performing motor imagery and passive movement using the haptic knob.

The NIRS setup measured 32 channels from 32 detectors for each source, which yielded a total of 1024 channels for each wavelength. The actual optobes locations were detected using the Xensor digitizer digitizer (A 3D electrode digitizer system used to capture the optobe locations that runs the optobes digitization procedure and records, visualizes and stores the digitized optobe positions). Only those channels with source and detector distances falling in 2.5cm to 4.0cm range were selected in this study. As a result, a total of 62 channels were used for each wavelength.

### C. Experimental Protocol

The subjects sat in a room with normal lighting on a comfortable chair with armrests. They faced a computer screen on which task cues were displayed and held the haptic knob with their right hand.. They were asked to relax before the data collection and during resting state. They were also asked to minimize physical movement, mouth movement and eye blinking through data collection process.

Due to the NIRS signal latency effect to hemodynamic response, where the peak response occurs approximately 5-8s post stimulus[15], the experimental protocol was designed to have a longer rest period(10s) after every action to make sure the signal of performing motor imagery and passive movement contains the peak values of hemodynamic changes were recorded. This is different from a typical EEG-based BCI experimental protocol design. Figure 3 shows the experimental protocol design of this study.

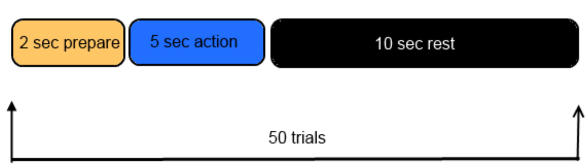


Figure 3. Experimental protocol design for multimadal NIRS and EEG-based motor imagery BCI. Action is motor imagery or idle in motor imagery run and passive movement or idle in passive movement run.

The experiment comprised of two runs, one for motor imagery and one for passive movement with 50 trials per run.

Actions are randomly selected as motor imagery or idle in motor imagery run, and passive movement or idle in passive movement run. Each trial started with a beep and a fixation cross as the visual cue was presented for 2s. Then a randomly generated action visual cue was presented for 5s. If a yellow arrow was presented, the subjects were asked to perform motor imagery of the right hand (open/close hand) in motor imagery run while passive movement of the right hand (open/close hand movement) was performed using the Haptic Knob robot in the passive movement run. If a yellow circle was presented, the subjects were asked to think blankly as the idle state. Followed by a dark blue status bar appeared for the rest period, and the subjects just relaxed.

### D. Data analysis

NIRS-SPM [12] is an emerging software for NIRS data processing and analysis. It is a SPM and MATLAB-based software package for statistical analysis of NIRS signals. NIRS_SPM uses modified Beer-Lambert law [16] to compute the concentration changes of HbO and HbR from optical density changes. It helps map the spatial registration of NIRS channels to MNI space. In this study the locations of the optobes were measured using Xensor digitizer. After the spatial registration of NIRS channel locations, the spatial registration of NIRS channels to MINI space with MRI coordinate input is available for further analysis. Statistical analysis of NIRS data adopted a mass-univariate approach based on the general linear model (GLM) and Sun's tube formula [12][17][18][19][20]. A high pass filter based on a discrete cosine transform (DCT) with a cutoff frequency of 80 Hz [21] and low pass filter hrf were used. The brain activation maps of HbO and HbR with super-resolution activation location were generated based on two contrasts: motor imagery versus idle and passive movement versus idle, with $p < 0.05$. Fig. 4 demonstrates the spatial location of the selected NIRS channels.

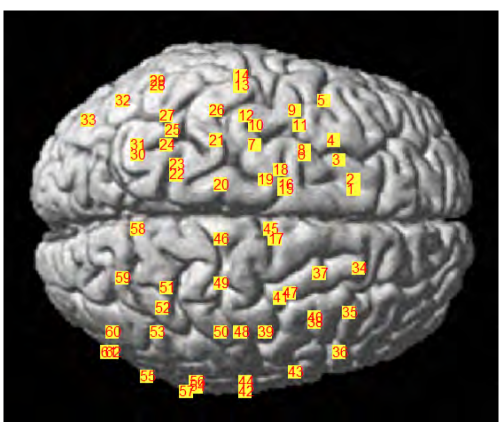

Figure 4. NIRS_SPM generated the spatial location of the selected channels.

This study investigated the classification accuracy on motor imagery versus idle and passive movement versus idle using the NIRS data as well. First, the data was normalized, and then low-pass filtered using Chebychev type II filter with a cut-off frequency of 0.14 Hz and pass-bank attenuation of 0.02 dB. Afterwards, linear-detrending was performed. The HbO and HbR were computed using Beer-Lambert Law [16]. The feature was effectively extracted using common average reference spatial filtering and single-trial baseline reference [13]. The discriminative features were selected using the Mutual Information-based Best Individual Feature (MIBIF) algorithm [22] and Support Vector Machine was used to classify the selected features. The performance was presented using 5x5-fold crossing-validation on the single-trial NIRS data.

EEG data was classified using the exact method in previous study [8]. Data was calibrated using the Filter Bank Common Spatial Pattern algorithm and the performance was computed based on a 10x10-folder cross-validation of the calibration data.

## III. RESULTS

Table I. shows the classification result on the EEG and NIRS data. The results showed that the average classification accuracies for passive movement versus idle are higher than for the motor imagery versus idle in both EEG data and NIRS data.

TABLE I. EXPERIMENTAL RESULTS ON THE CLASSFICATION OF NIRS AND EEG DATA.

| Subject | EEG Data | | NIRS Data | |
|---|---|---|---|---|
| | *MI vs Idle* | *PM vs Idle* | *MI vs Idle* | *PM vs Idle* |
| 1 | 49.9 | 80 | 53.6 | 65.2 |
| 2 | 73.9 | 92.8 | 54.2 | 64.8 |
| 3 | 54.8 | 56.8 | 57.4 | 67.2 |
| 4 | 60 | 59.9 | 45.8 | 43.6 |
| Mean | 59.65 | 72.375 | 52.75 | 60.2 |

Fig. 5 shows the motor area activations during motor imagery and passive movement with contrasts defined as motor imagery versus idle and passive movement versus idle of individual analysis. The left side shows the activation of HbO with the contrasts of motor imagery versus idle and the right side shows the contrasts of passive movement versus idle, with $p < 0.05$.

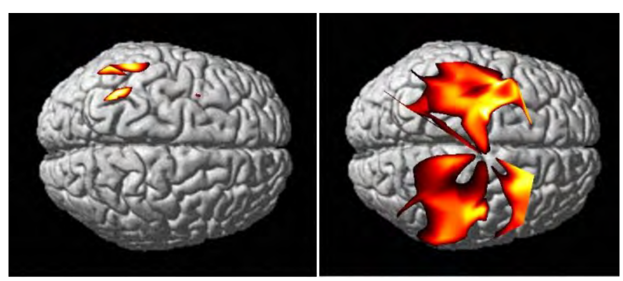

Figure 5. Individual motor area activations of HbO with contrasts of motor imagery versus idle and passive movement versus idle (from left to right), $p < 0.05$.

The results show that passive movement induces obvious changes in brain activity in both the right and left motor area while motor imagery movement only induces less obvious changes in left motor area.

## IV. DISCUSSION AND CONCLUSIONS

This study investigated the primary sensorimotor area activation from fNIRS on 4 subjects using multimodal NIRS and EEG-based BCI system while performing motor imagery and passive movement of the hand througgh a Haptic Knob robot. The NIRS and EEG data were collected simultaneously. The design of this study is based on the use of EEG-based motor imagery brain-computer interface for neurorehabilitation in stroke [23].

The results of the activations on the contrasts showed that passive movement versus idle yielded significant differences compared to motor imagery versus idle. For the activations on the contrasts of passive movement versus idle, 3 of 4 subjects showed the activations on both right and left area. However, the reasons as to why passive movement induced obvious changes in brain activity in both the right and left motor area are worth further investigation to better understand the fundamental neural basis of the human brain. We will investigate this on more subjects.

Apart from the motor area activation map, the results of the classification of the NIRS and EEG data also showed that the accuracies on classifying passive movement versus idle are better than that of motor imagery versus idle.

The performance of motor imagery is internal to the subject and there is no direct way to observe this performance; on the other hand, the performance of passive movement is easy to observe directly. The results suggest a potential of using passive movement data to calibrate motor imagery in a multimodal NIRS and EEG-based BCI.

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