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Functional Near-Infrared Spectroscopy based Discrimination of Mental Counting and No-Control State for Development of a Brain-Computer Interface

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***Abstract*— In this paper we propose to apply functional near-infrared spectroscopy (fNIRS) to measure the brain activity during mental counting and discriminate it from the no-control (rest) state, which could potentially lead to a two-choice brain-computer interface (BCI) application. fNIRS is a relatively new optical brain imaging modality that can be used for BCI. The major advantages using fNIRS are its relatively low cost, safety, portability, wearability and overall ease of use. In the present research, five healthy subjects are asked to perform mental counting during the activity period. Signals from the prefrontal cortex are acquired using a continuous-wave imaging system. The mental counting and no-control states are classified, using linear discriminant analysis (LDA), with an average accuracy of 80.6%. These classified signals can be translated into control commands for a two-choice BCI. These results show fNIRS to be a potential candidate for BCI.**

I. Introduction

The aim of a brain-computer interface (BCI) is to allow people with locked-in syndrome to communicate with and control a computer or an external device through the process of thinking [1,2]. Methods of brain signal acquisition for BCI can be invasive and noninvasive. The invasive methods acquire brain signals by implanting electrodes into the gray matter of the brain in a surgical procedure while the noninvasive methods don't used any surgical procedure for acquiring brain signals. In the previous studies, the possibility of multidimensional control over external devices has been shown using the invasive methods [2,3], however, the same is still a challenge using noninvasive methods. Some of the non-invasive brain-imaging modalities are Functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET), Electroencephalography (EEG), Magnetoencephalography (MEG), Single Photon Emission Computed Tomography (SPECT) and Functional Near-Infrared Spectroscopy (fNIRS). fMRI and fNIRS give information about the hemodynamic changes caused by the neural activity in the cortical regions of the brain while PET and SPECT quantify radioactivity concentrations to provides information about the brain activity. We choose fNIRS for brain signal acquisition because of its advantages of being safe, portable, wearable and cheap. The measurement principle of fNIRS was first reported in 1977 by Jobsis [4]. Since then, although it has been used to study the cerebral hemodynamic, it is being studied for BCI in the last few years only [5,6,7,8,9].

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In this research we measured and classified brain activity as "mental counting" and "no-control" during mental counting task. The two states were decoded with an average classification accuracy of 80.6% using the linear discriminant analysis (LDA).

II. Material and Methods

A. Signal Acquisition

fNIRS uses the light in the near infrared range (650 nm ~ 1000 nm) that can penetrate in the human tissues. A near-infrared light emitter is used to incident light on the scalp. The light induced travels through the head having multiple scattering and passes through the cortical areas of the brain where oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR) are present. HbO and HbR absorb light with different absorption coefficients for different intensity of light as shown in Fig. 1. Some of the photons, reflected back after scattering and absorption by the HbO and HbR, are detected using a detector placed on the scalp. The modified Beer-Lambert law is then used to calculate the changes in concentration of HbO and HbR.

$$\begin{bmatrix}\Delta\phi_{\mathrm{HbO}}(t)\\ \Delta\phi_{\mathrm{HbR}}(t)\end{bmatrix} = \begin{bmatrix}a_{\mathrm{HbO}}(\lambda_1) & a_{\mathrm{HbR}}(\lambda_1)\\ a_{\mathrm{HbO}}(\lambda_2) & a_{\mathrm{HbR}}(\lambda_2)\end{bmatrix}^{-1} \begin{bmatrix}\Delta\phi(t;\lambda_1)\\ \Delta\phi(t;\lambda_2)\end{bmatrix}, \quad (1)$$

$$\Delta c_{\mathrm{HbX}}(t) = \frac{\Delta\phi_{\mathrm{HbX}}(t)}{dl}, \quad (2)$$

where $\Delta\phi_{\mathrm{HbX}}(t)$ is the optical density variation of HbX in μMmm, $\Delta\phi(t;\lambda_j)$ (j =1,2) is the unit-less total optical density variation of the light emitter of wavelength λ_j, $a_{\mathrm{HbX}}(\lambda_j)$ is the extinction coefficient of HbX in $\mu M^{-1}mm^{-1}$, d is the unit-less differential pathlength factor, and l is the distance (in millimeters) between emitter and detector.

We used continuous wave NIRS system DYNOT (Dynamic Near-Infrared Optical Tomography), at a sampling rate of 1.81 Hz to acquire brain signals. This system was obtained from NIRx medical technologies, LLC, New York. The system uses near-infrared lights of two wavelengths i.e. 760 and 830nm shown in Fig. 1. Both wavelength lights were used to get the concentration changes of HbO and HbR.

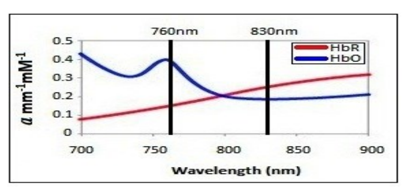

Figure 1. Absorption coefficients, of HbO and HbR, for different wavelengths of near-infrared light.

B. Subjects

Five subjects (mean age: 30.2 ± 2.38) participated in the experiments. None of them had a history of any psychiatric, neurological or visual disorder. All of them had normal or corrected-to-normal vision, and they all provided verbal informed consent. The experiments were performed in accordance with the latest Declaration of Helsinki.

C. Optode Placement

Two emitters and six detectors were placed on the prefrontal cortex of all subjects to measure the brain signals. The optode placement and channel configuration is shown in the Fig. 2. The red-filled squares represent the two emitters and the circles represent the 6 detectors used. The selected channels with the emitter-detector separation of 3 cm, considered for the analysis, are numbered. The source-detector distance of 3 cm was used is in accordance in the literature [10]. The channels with an emitter-detector distance of more than 3 cm were discarded as they might not contain useful information because of their high emitter-detector separation.

D. Experimental Paradigm

The subjects were seated in a comfortable chair facing a monitor placed at a distance of 65-70 cm. During the activity period, they were asked to mentally count the number of times a screen is changed on the monitor. The experimental sequence illustrated in Fig. 3 is explained below:

1. The first 20 s was a rest period to set up the baseline conditions.
2. In the next 20 s the subjects were required to perform mental counting.
3. The last 20 s was again a rest period to settle the signal values to baseline.

The above sequence was repeated 20 times for each subject. The total duration of the experiment for each subject was hence 800 s. Each subject performed five trials.

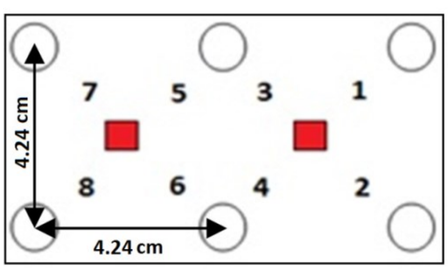

Figure 2. Optode placement and channel configuration.

E. Signal Processing and Classification

The raw intensity signals contain high frequency components such as heart beat [11]. To remove these, low-pass filtering was done on the raw intensity signals using the signal processing toolbox of Matlab. After filtering, the signals were normalized by dividing the signals with the mean of the baseline signals over one trial. Using (1) and (2), ΔHbO and ΔHbR was then calculated. After filtering and normalization, the classification was carried out on the HbO and HbR signals. The objective of classification is to classify the subjects' state as "mental counting" and "no-control". Linear discriminant analysis (LDA) was used as the classifier. LDA is a linear classifier which uses hyper planes to discriminate between the data that represent two different classes. The values of concentration changes in HbO and HbR from the selected channels (having source-detector distance of 3 cm) for specific time points (activity period) were used as features to the classifier. Table I shows the average classification accuracies of all subjects over five trials.

III. RESULTS

The normalized and filtered signals, of change in concentration of HbO and HbR, are shown in Fig. 4. It can be seen that the concentration change in HbO was higher during the activity period from 20 s to 40 s than during the rest periods. The classification accuracy using the LDA for the mental counting, averaged over all channels and for all subjects, was 80.6% as shown in the Table I. The lowest average classification accuracy was found to be 79.4% for Subject 1 while the highest one was 82.1% for Subject 5. A two-dimensional feature space for subjects 2 and 5 are shown in Fig. 5 and Fig. 6 respectively. The red crosses indicate the mental counting while the blue circles indicate the no-control state. The blue line represents the decision boundary between the mental counting and no-control states.

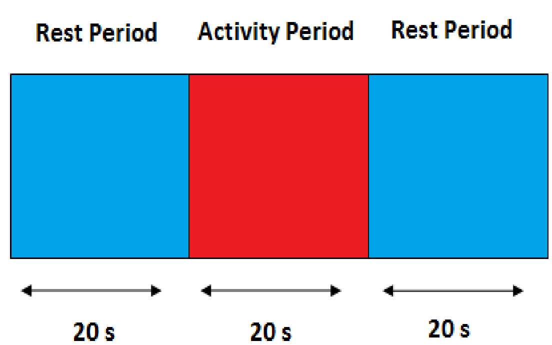

Figure 3. Experimental paradigm: The two blue box at the beginning and at the end show 20 s rest period while the red box in the middle shows the 20 s mental counting period.

Table I.
LDA CLASSIFICATION RESULTS FOR THE EXPERIMENT

Subject	Trial					
	1	*2*	*3*	*4*	*5*	**Average**
1	82.1%	76.8%	79.2%	81.0%	78.2%	79.4%
2	78.3%	84.2%	80.2%	79.2%	83.3%	81.0%
3	79.8%	77.5%	82.1%	79.3%	83.2%	80.3%
4	82.5%	80.5%	78.2%	80.7%	81.5%	80.6%
5	85.2%	82.1%	80.2%	79.0%	84.1%	82.1%
						80.6%

IV. DISCUSSIONS

In this research we successfully decoded brain state as "mental counting" or "no-control" for mental counting experiments with an average classification accuracy of 80.6% across five subjects. This result shows the feasibility of using fNIRS for BCI.

An important factor to be noted is that all the subjects of this investigation were healthy. The hemodynamic response of people with amyotrophic lateral sclerosis, tetraplegia or other motor or speech impairments can differ from those of healthy subjects, which can result in relatively low classification accuracies.

In our previous study [12], it was shown that using fNIRS, it is possible to decode the "active" and "rest" states with an average classification accuracy of 73.6% for a finger tapping experiment. A source-detector distance of 2.12 cm was used and average values of concentration change in HbO and HbR were used as features. In this study, however, by using a source-detector separation of 3 cm and more enhanced feature, concentration changes of HbO and HbR from the selected channels for specific time points, higher classification accuracies are achieved.

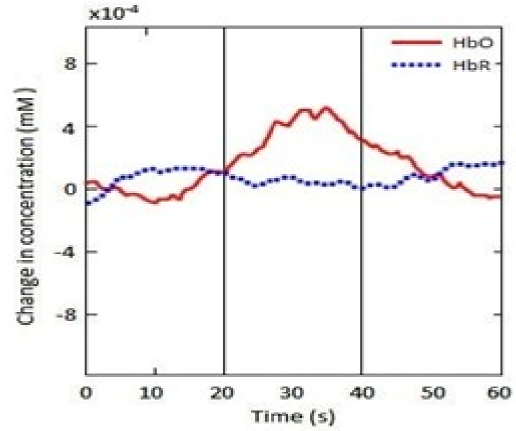

Figure 4. Concentration changes in HbO and HbR signals for the experiment. (Channel 4, Subject 3).

The classification accuracies can be further increases using different classifiers, different features and adaptive filtering techniques [13,14].

V. CONCLUSIONS

In this research we showed that it is possible to discriminate, with high classification accuracy, between the brain signals due to mental counting and no-control state using fNIRS. The classified signals can then be translated into control commands for a two-choice BCI. The results of this research successfully prove fNIRS to be a potential candidate for BCI applications. In future we aim to go one step further from binary classification to multiple classifications of different brain activities to achieve multidimensional control of external devices such as robots or other prosthesis devices.

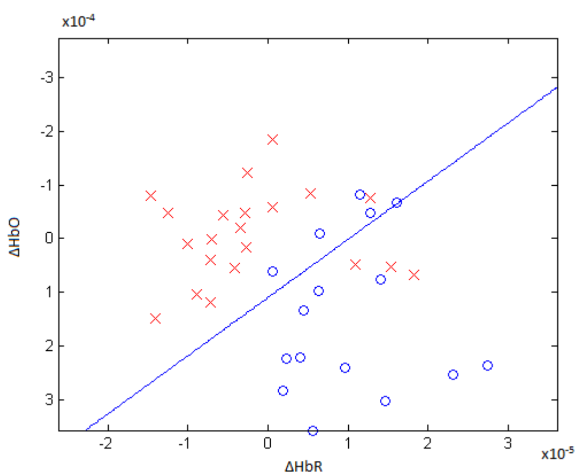

Figure 5. Two-dimensional feature space for Subject 2 for the experiment: The crosses indicate the mental counting and the circles indicate the no-control state.

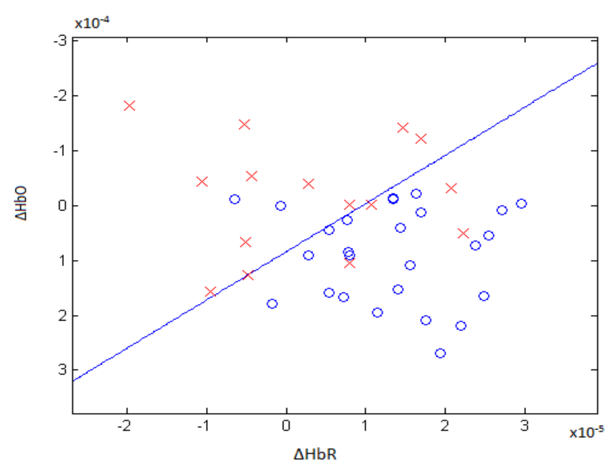

Figure 6. Two-dimensional feature space for Subject 5 for the experiment: The crosses indicate the mental counting and the circles indicate the no-control state.

Acknowledgment

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