Assessment of Cognitive Neural Correlates for a Functional Near Infrared-Based Brain Computer Interface System

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Abstract. Functional Near Infrared Spectroscopy (fNIR) is a promising brain imaging technology that relies on optical techniques to detect changes of hemodynamic responses within the prefrontal cortex in response to sensory, motor, or cognitive activation. fNIR is safe, non-invasive, affordable, and highly portable. The objective of this study is to determine if biomarkers of neural activity generated by intentional cognitive activity, as measured by fNIR, can be used to communicate directly from the brain to a computer. A bar-size-control task based on a closed-loop system was designed and tested with 5 healthy subjects across two days. Comparisons of the average task and rest period oxygenation changes are significantly different ($p<0.01$). The average task completion time (reaching +90%) decreases with practice: day1 (mean 52.3 sec) and day2 (mean 39.1 sec). These preliminary results suggest that a closed-loop fNIR-based BCI can allow for a human-computer interaction with a mind switch task.

Keywords: Brain Computer Interface, fNIR, Near Infrared Spectroscopy.

1 Introduction

The purpose of this research is to develop a new functional Near-Infrared (fNIR) based Brain Computer Interface (BCI) to allow communication directly from the brain to a computer. In this paper, we have reported the implementation and initial results of a closed-loop fNIR based BCI system and the analysis methods that allow classification of two states (rest and task) using single channel two wavelength optical signals.

An individual's communication with the outside world can cease because of complete paralysis, locked-in syndrome, spinal cord injury or muscular dystrophy. Individuals suffering from such diseases and conditions, though conscious, may lose all voluntary muscle control and thus are often unable to communicate even their most basic wishes [1, 2]. Unlike a persistent vegetative state, in which the upper portions of

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the brain are damaged and the lower portions are spared, an inability to move may be caused by damage to specific portions of the lower brain and brainstem or to muscles with no damage to the upper brain. Consequently, an individual's cognitive abilities remain relatively intact [2-4].

BCI is defined as a system that translates neurophysiological signals detected from the brain to supply input to a computer or to control a device. BCI research largely targets to eliminate the need for motor movement and develop mechanisms to relay information directly from the brain to a computer which, in turn, can be used to control or communicate with outside world. In addition to their use in neuroprosthetics, noninvasive BCI systems also have potential applications for healthy individuals especially for enhancing or accelerating the learning process, or in entertainment domains such as in computer games and multimedia applications as a neurofeedback mechanism. Development of alternative communication strategies are a recognized need for clinical applications. A technique that bypasses muscles and acquires signals directly from brain would be a notable help. Moreover, this technique should be minimally intrusive, non-invasive, accessible, and safe to be used continuously.

1.1 Monitoring Brain Activity

The key element in a BCI system is monitoring brain activity. There are several available technologies that utilize different sensors or sensor configurations to collect various types of brain signals.

The most commonly studied interface to monitor brain activity noninvasively has been Electroencephalogram (EEG), due to its fine temporal resolution, portability and low cost [5-10]. Various electrode placement schemes and advanced signal processing methods have been researched for its improved and practical use in BCI applications [11]. However, these EEG based systems still have certain drawbacks. For example, the end-user has to develop a new thinking mechanism to be able to interact with the EEG based BCI system which results in lengthy training times [12]. Furthermore, non-invasive EEG recordings from portable devices are highly susceptible to noise and hence have much lower signal to noise ratio as compared to signals recorded from implanted electrodes [13]. In addition, electrode fixation is difficult and cumbersome to use in practice and for long-term use because of the need for applying gel and the restrictions on users' movements. Therefore, existing BCI systems do not yet meet the desired characteristics of an optimal BCI. In fact, they are either invasive and hence not yet completely safe for continuous use or they are non-invasive but rely on a noisy signal and require mental adaptation mechanisms.

Another potential neuroimaging modality is functional Magnetic Resonance Imaging (fMRI) which is a special type of MRI scan that measures the hemodynamic response to neural activity. Recently, this technique has been improved to be used at real-time in which output of the system could be used to give biofeedback to the subject, thus creating a closed-loop system. It has been shown using real-time functional magnetic resonance imaging (rt-fMRI) that subjects can voluntarily change activation/oxygenation levels of certain brain regions [14-22]. This technique is non-invasive and allows detecting signals anywhere in the brain, and thus provides more flexibility for the BCI mental task. However, the downside is that participants have to

be scanned in large and expensive MRI machines and thus may not be practical for daily and long-term use.

In order to partially overcome the problems of existing BCI and provide an alternative communication mechanism for individuals with locked-in syndromes, we propose to use continuous wave fNIR as a new functional neuroimaging modality for Brain Computer Interface. In the next section, we will briefly discuss the fundamentals of fNIR, types of fNIR instrumentation and other BCI studies that have utilized fNIR.

2 fNIR Spectroscopy

fNIR is a multi-wavelength optical spectroscopy technique introduced as a non-invasive brain activity monitoring modality [23-27]. fNIR can assess temporal progression of brain activity, through the measurement of hemodynamic changes within reasonable spatial resolution. Neuronal activity is determined with respect to the changes in oxygenation since variation in cerebral hemodynamics are related to functional brain activity through a mechanism which is known as neurovascular coupling [26]. fNIR is not only non-invasive, safe, affordable and portable [28, 29], it also provides a balance between temporal and spatial resolution which makes fNIR a viable option for in-the field neuroimaging.

2.1 Light Tissue Interaction

Typically, an optical apparatus for fNIR Spectroscopy consists of at least one light source and a light detector that receives light after it has interacted with the tissue. Photons that enter tissue undergo two different types of interaction: absorption and scattering [30]. Whereas most biological tissues (including water) are relatively transparent to light in the near infrared range between 700 to 900 nm, hemoglobin is a strong absorber of lightwaves in this range of the spectrum.

Two chromophores, oxy- and deoxy-Hb, are strongly linked to tissue oxygenation and metabolism [26]. Fortuitously, the absorption spectra of oxy- and deoxy-Hb remain significantly different from each other allowing spectroscopic separation of these compounds to be possible by using only a few sample wavelengths. Once the photons are introduced into the human head, they are either scattered by extra- and intracellular boundaries of different layers of the head (skin, skull, cerebrospinal fluid, brain, etc.) or absorbed mainly by oxy- and deoxy-Hb. If a photodetector is placed on the skin surface at a certain distance from the light source, it can collect the photons that are scattered and thus have traveled along a “banana shaped path” from the source to the detector [23, 25, 26].

2.2 Types of fNIR Systems

A wide variety of both commercial and custom-built fNIR instruments are currently in use. There are three distinct types of fNIR spectroscopy implementations; time-resolved (TR), frequency domain (FD) and continuous wave (CW) systems, each with its own strengths and limitations. TR and FD systems provide information on shifts in

both phase and amplitude of the light and are necessary for more precise quantification of fNIR signals. Lasers are used as light sources and fiber optic light guides are utilized in sensors. CW systems apply either continuous or a slow-pulsed light to tissue and measure the attenuation of amplitude of the incident light. These systems utilize less sophisticated detectors than TR and FD systems, and, therefore, they cannot determine the pathlength the photons have traveled. As such, CW systems provide only a measure of the relative change in light intensity Although CW systems provide somewhat less information than TR and FD systems, this tradeoff results in the capacity to design more compact and inexpensive hardware, making it advantageous for real-life applications [31]. CW system can use Light-Emitting-Diode (LED), instead of Laser, as light sources and do not necessarily require fiber optics in sensors, making them less expensive and more comfortable to wear for longer periods of time.

2.3 fNIR in BCI Research

There is recent evidence indicating that fNIR can be used for the assessment of attention [32] and cognitive task loads [33]. Recently, the suitability of optical methods for BCI has been investigated by acquiring signals from the motor cortex using motor imagery tasks [12, 13, 34, 35] and by acquiring signals from the frontal cortex by mental arithmetic [36] and cognitive workload [37-39] tasks. Taken together, the results of these studies have focused on offline analysis and use either FD-fNIR or laser with fiber optics. The overall aim is to build a CW-fNIR based BCI system that will be operated by the volitional activation of the prefrontal cortex assisted by neural biofeedback. As a first step, we have investigated the potential of fNIR in discriminating cognitive activity levels based on different tasks. Our results suggest that with a CW-fNIR system, we can detect increased oxygenation within the frontal lobe with increased cognitive task load [38]. In this study, we have investigated a closed-loop feedback regulated CW-fNIR based system.

3 Materials and Methods

3.1 Drexel fNIR System

The CW-fNIR system used in this study has a flexible sensor pad that contains 4 LED light sources with built in peak wavelengths at 730, 805, 850 nm and 10 detectors designed to sample cortical areas underlying the forehead (See Fig. 1). With a fixed source-detector separation of 2.5 cm, this configuration generates a total of 16 measurement channels per wavelength. The sampling rate of the system is 2Hz [32, 40, 41].

3.2 Experiment Setup

The experimental setup is composed of a Protocol-Computer, a Data-Acquisition computer and the Drexel fNIR system parts as described in Fig. 1. The fNIR sensor is positioned on the subject that is sitting in front of the Protocol Computer as shown in Fig. 2.

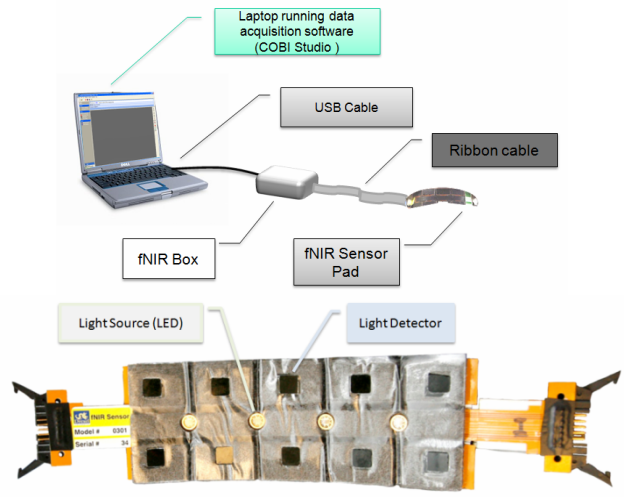

Fig. 1. Drexel fNIR System Parts

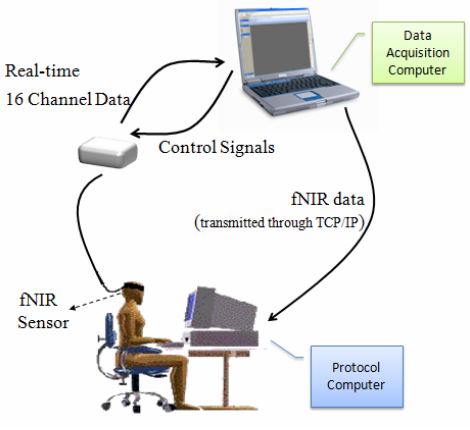

Fig. 2. Experiment Setup

Information flow starts from at the fNIR Sensor and through the control box, reaches the Data-Acquisition Computer. COBI Studio software [41] collects raw fNIR signals for 16 channels and 2 wavelengths and transmit them through Ethernet or wireless network (via TCP/IP) to the Protocol Computer. The BCI Client software on the Protocol-Computer receives the raw fNIR signals, calculates the oxygenation changes at run-time using modified Beer Lambert Law and modifies the visual feedback which in turn changes the fNIR signals at sensor; thus completing the closed loop.

3.3 Participants

Five healthy right-handed subjects (4 males, 1 female) with no neurological or psychiatric history (ages between 24 to 27years) voluntarily participated in the two-day

study. Handedness was assessed by the Edinburg Handedness Inventory [42]. All subjects gave written informed consent approved by the institutional review board of Drexel University for the experiment.

3.4 Experiment Protocol

A computerized task, called bar-size-control was developed to control the timing, display the visual feedback and to save user input. In a single trial, subjects are first asked to rest for 20 seconds with a blank screen, after which a vertical or horizontal bar will appear (See Fig. 3.).

Fig. 3. Horizontal/vertical bar cue shown full-screen. The bar size is changed every 500 milliseconds according to the oxygenation changes of the subjects.

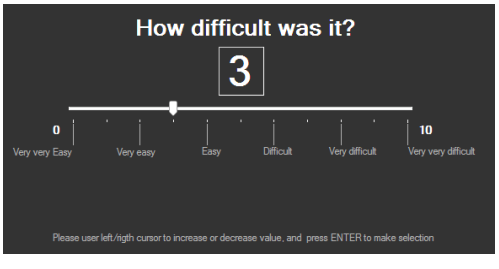

Fig. 4. Self-assessment screen is shown at the end of each trial. Subjects use left/right cursor buttons to change the value and press enter to select the value.

Initially, the bar is at 50 percent size and is mapped to the oxygenation data calculated from fNIR data that is updated at a frequency of 2Hz. The subject is asked to concentrate on the bar for up to 120 seconds. Finally, the subject is asked to rate their effort on scale from 0-10 with 0 lowest and 10 highest effort/difficulty (See Fig. 4.) [43]. The subject has 30 seconds to complete this effort rating activity. Each trial lasts a maximum of 170 seconds.

3.5 Signal Analysis

There are two types of signal processing in this study. The first one is online processing, that is done during the experiment, and the second one is offline processing that is completed after the experiment to analyze the data. Both online and offline analyses include calculation of oxygenation changes from raw data using the following steps [31, 32].

The raw optical intensity values in two wavelengths (730nm and 850nm) are transmitted and recorded by the fNIR system for all subjects. The physiologically irrelevant data (such as respiration and heart pulsation effects) and equipment noise,

and so forth is first eliminated from the raw fNIR measurements by using a low-pass filter with a cut-off frequency of 0.14Hz.

The online processing further involves calculating the visual cue size based on the oxygenation changes during the experiment. Size of the vertical or horizontal bar is modeled as a linear transformation of the oxygenation changes of channel 6 that corresponds to a voxel location close to Fp1 in the international 10-20 system. Bar(t) is the bar size as a function of time t, where t_n is the time when the bar task started. BaseOxy for channel 6 and time t_n is calculated by the moving average of the last k oxygenation change values for the same channel multiplied by the constant α which is the difficulty parameter. α= 1.5 was used for all subjects.

$$Bar(t) = \left(Oxy_6(t) - BaseOxy_6^{t_n}\right) / Range_6^{t_n} * Width. \quad (1)$$

$$BaseOxy_6^{t_n} = (1+\alpha) / k \sum_{i=1}^{k} Oxy_6(n-i). \quad (2)$$

$$Range_6^{t_n} = 2\,\alpha\; BaseOxy_6^{t_n} \quad (3)$$

For the offline processing blocks for rest and task conditions were identified for day1 and day2 of each subject. Averages of oxygenation changes in rest and task performing blocks where compared with a-repated measures ANOVA model. Furthermore, select non-parametric classification algorithms and their success rates on the available data have been applied. These techniques enable classifying a set of observations into predefined classes which in our case are task performing or resting conditions. To classify the blocks with a linear and quadratic discriminant algorithm a subset of data is used as training set. k-Nearest neighbor search (k-NN) and naive Bayes classifier (MATLAB 2008a, MathWorks Inc.) were used with day1 as training and day2 as sample, and also, half of day2 as training and the rest of day2 as sample.

4 Results and Discussion

For the computerized task, a bar was chosen for its simplicity and familiarity to all computer users. Experiments are ongoing. Comparisons of the means for task and rest period oxygenation changes are significantly different ($p<0.01$). The average task completion time (reaching +90%) decreases with practice: day1 (mean 52.3 sec) and day2 (mean 39.1 sec) across all subjects. This suggests learning and adaptation is in process.

During offline processing, blocks (rest and task periods within days) are classified with the following non-parametric algorithms: k-Nearest Neighborhood and naïve Bayes classifier. For the classification the first 16.5 seconds of each block is used. First, the algorithms are trained with the Day1 task and rest periods block data and asked to identify Day2 blocks whether they are task and rest. This was done for each subject individually and also for all subjects. The results are listed in column A in Table 1.. Next the same analysis is done with a different training set, instead of Day1, the first half of the Day2 data (task and rest periods) was used. Thus, condition B has half of the training and sample size of the previous condition. Correct classification

success rates are listed in column B of Table 1.. Algorithms were unbiased and did not include the behavioral performance score or the self reported performance score. The success rate of algorithms varies between subjects suggesting that some subjects are better at using the closed loop system than other subjects. Also, column B indicates a lower success rate which in turn might be related to a lower training set than column A. Overall classification rates suggests a pattern across subjects and using the training data from all subjects provides a better chance of correct classification than individual subjects classification.

Table 1. Classification algorithm performances as percentage of correct classification in two conditions: A and B. The first condition A has training set Day1 and sample set as Day2. Second condition has training set as the first half of Day2 and sample set as second half of Day2.

	A				B			
	kNN		Bayes		kNN		Bayes	
	Rest	Task	Rest	Task	Rest	Task	Rest	Task
Subj1	100	100	100	100	100	90.9	100	90.91
Subj2	100	100	100	100	93.75	68.75	87.5	68.75
Subj3	100	80	70	55	72.72	63.64	90.1	54.55
Subj4	75	70	100	60	63.64	100	90.9	100
Subj5	80	56.67	100	100	75	68.75	87.5	75
Overall	93.3	72.5	100	95	77.1	73.77	86.89	57.37

5 Conclusion

In this study, we have reported the implementation and initial results of a closed-loop fNIR based BCI system along with the analysis methods that allows classification of two states (rest and task) using only fNIR signals. This system can be used for binary selection with volitional activation of the prefrontal cortex. Further experiments are pending to study and improve the use of algorithms for online classification.

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