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Classification of brain hemodynamic signals arising from visual action observation tasks for brain–computer interfaces: A functional near-infrared spectroscopy study

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ABSTRACT

A brain–computer interface (BCI) is a way of translating an individuals' thoughts to control a computer or an external mechanical device. Studying brain activities in a reproducible manner, this study explores the possibility of using real-time functional-near infrared spectroscopy (fNIRS) to detect brain hemodynamic features for BCI commands. Sixteen channel brain activities associated with two distinct mental tasks were measured from seven healthy subjects. The tasks represented neural activities arising from a visual observation of a motor action related to hand movements of the subjects. Sensitive signatures of task relevant neural activities were further extracted from hemodynamic signals in the prefrontal cortex of the brain, and subsequently were translated into pre-determined computer commands using a set of algorithms. The decoded commands allowed volunteer subjects to control an external device in real-time through their mental intentions. The obtained results demonstrate the potential of the current study as an alternative fNIRS-BCI paradigm.

1. Introduction

Recent studies have manifested the potential of functional near-infrared spectroscopy (fNIRS) as an alternative BCI modality having attractive characteristics over the other systems [1–3]. The method of fNIRS presents neural information which is related to cortical hemodynamics and oxygenation status during functional brain activities through concentration levels of oxy- and deoxy-hemoglobin chromophores of the brain (denoted as oxy-Hb and deoxy-Hb) [4,5]. These oxy-Hb and deoxy-Hb concentration parameters provide important information on subjects' cognitive state and can be mapped into external BCI commands [6].

To date most fNIRS based BCI studies have been performed offline in order to decode mental task relevant hemodynamic responses. For instance, Sitaram et al. demonstrated the decoding of brain hemodynamics arising from right- and left-hand motor imagery from five subjects [7]. In their study the authors achieved nearly 90% classification accuracy for motor imagery tasks. Sassaroli et al. showed successful classification of brain hemodynamics from five mental tasks using a simple k-means algorithm [8]. Other offline studies, for instance, have proposed a neural network approach for the classification of fNIRS signals [9] or other sophisticated machine learning methods to assess the classifiability of fNIRS signal features [10,11]. Most of these studies have produced results in the range of 70%-90% classification accuracy. These initial off-line studies were necessary to demonstrate fNIRS as a BCI modality, however for any practical BCI, it is still important to be able to operate on-line with the classifier outputs being produced in real-time. Only a few researchers have attempted to use fNIRS signals in on-line settings relying on different BCI paradigms. Coyle et al. first proposed an on-line fNIRS-BCI system which was based on discrimination concentrations of hemodynamic changes

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during a motor imagery task and a baseline measurement [12]. Utsugi et al. presented a real-time BCI control of a toy train using an online classifier [13]. Their classifiers were trained in a calibration mode to generate control commands to activate the train. The study presented by Abdelnour and Huppert [14] used a direct topographic map of oxy-Hb and deoxy-Hb over the motor cortex to classify between left and right finger tapping with classification rates ranging from 68.8% to 93.8%.

Most of the aforementioned studies exhibit potential in the emerging field of fNIRS-BCI research. However, there is still a significant work to be performed before this technology can be fully used in practice [15,16]. For instance one needs to investigate efficacy of synchronous or asynchronous BCI paradigms, where the synchronous BCIs use external cues on a monitor (or sounds such as tones or words) and in the in contrast the asynchronous requires no attention to specific stimuli to operate devices. In addition, it is still not fully explored whether literal or interpretive BCIs approaches are appropriate for optimal control. With the literal BCI subject's intent could be translated literally to an output (e.g. subject thinks of moving her left arm up, and this moves a prosthetic arm up). While in the interpretive BCI, the user performs mental activities unrelated to the task (e.g. a user may imagine singing, or detect specific flashes, to move a prosthetic arm up). In [13], subjects performed a complex mathematical task to control a toy train, and thus the user's intent is not directly translated into output, hence their approach belongs to the interpretive BCIs.

The current work aims to contribute to the same efforts of developing a synchronous fNIRS-BCI paradigm using an action observation tasks. The tasks that closely resembles to the mirror neurons concept which represents a neural activity that arises when we see someone else performing a complex motor action, and when we imagine ourselves performing the same action. Our empirical analysis, throughout offline and online experiments, has shown that these tasks can be decoded with a reasonable accuracy as BCI commands.

Besides the experimental paradigm the signal processing, the feature extraction and the machine learning techniques play an important role in every BCI research [17,18]. In fact, many research efforts have been focused on these algorithmic steps; since the algorithms allow to extract sensitive signatures of neural signals in which human intentions are best encoded. This study assess the performances of robust linear programming based support vector machine classifiers. The details of each step is provided in the rest of the article as follows (see Fig. 1). Section 2 describes the experimental framework used for fNIRS data acquisition. Section 3 presents signal pre-processing and classification algorithms for decoding subjects' neural signals. Section 4 presents the results from the offline and online BCI experiments. Finally, Section 5 presents our conclusions.

2. Materials and methods

2.1. Data acquisition

A continuous type optical brain-function imaging system fNIR-300 (BIOPAC Systems Inc., USA) has been used for data acquisition. The system has a flexible sensor consisting of 4 light sources having 3 built in laser diodes emitting different wavelengths of 730 nm, 805 nm, and 850 nm and 10 detectors designed to image cortical areas underneath the forehead. With a fixed source-detector separation of 2.5 cm, this configuration generated a total of 16 signal channel measurements with a sampling rate of 2 Hz.

Seven right-handed healthy subjects, one female and six males (age range 22–32 years old) participated in this study. Only two of the subjects had previous experience in BCI imagery experiments.All study participants gave informed consent. The ethical approval of the research was granted by the research ethics committees of the Daegu-Gyeongbuk Institute of Science and Technology.

Sixteen channels concentration levels of Oxy-Hb, deOxy-Hb, and total-Hb were measured with every participants. The optical fiber probes were placed on the pre-frontal cortex of the participants according to the 10–20 international electrode placement system [19]. Fig. 2(a) shows the locations of the transmitter laser diodes and receiver optodes which correspond to the left frontal region (Fp1-Ch8, AF3-Ch7, AF7-Ch6, F1-Ch5, F3-Ch3, F5-Ch1, F7-Ch4, F9-Ch2) and to the right frontal region (Fp2-Ch10, AF4-Ch9, AF8-Ch12, F2-Ch11, F4-Ch13, F6-Ch15, F8-Ch14, F10-Ch16) of the brain cortex. The red-colored numbers represent the transmitters, and the blue-colored numbers represent the receivers; the yellow circles show the locations of the 16 channels. In this study, our analysis is based Oxy-Hb signals because the changes in the concentration levels of oxy-Hb are highly correlated with the regional cerebral blood flow (fCBF) and an increase in rCBF reflects an increase in neural activity [20,21].

2.2. Experimental paradigm

The data recording sessions were organized into eight sessions with one session per day. Four of the eight sessions were set for performing the task of [rest → right imagery task] and the remaining four sessions were organized for [rest → left imagery task]. Each session was further divided into two blocks. The duration of each task block in a session was set to 180 s. During the rest block, participants were asked to sit and relax and not perform any task; the signals obtained during this relaxation period were used as a reference in the classification task. In task blocks, participants were instructed to perform an imagery movement task of their right forearm in the right and left directions. This mental task was performed simultaneously with a given visual observation task. The visual observation task consisted of an action movie clip showing the movement of the participants' forearms in the intended direction. Each movement in the clip was repeated every two seconds, which made up a total of 90 consecutive repetitions of the forearm movement. Fig. 2(b) provides more details on the data acquisition paradigm. Fig. 3 shows an example of measured signals from subject 1 corresponding to the right movement imagery task.

The presented experimental paradigm appears rather different from well known motor imagery or cue-based BCI paradigms. Here, we investigate another approach with