Design of Differential Near-Infrared Spectroscopy Based Brain Machine Interface

S. Senthilkumar¹, T. Shanmugapriya²

Assistant Professor, Department of Electronics and Instrumentation, Bharath University, Chennai, Tamil Nadu, India¹
Assistant Professor, Department of Information Technology, SSN Engineering College, Chennai, Tamil Nadu, India²

ABSTRACT: Near-Infrared Spectroscopy (NIRS) is a non-invasive technology for measuring brain activity. Recently, the number of research papers on Brain Machine Interface (BMI) based on NIRS technology is increasing. NIRS is a safe and convenient technique but its measurement results are unstable. To improve reliability of NIRS-based BMI, methods to extract stable data from NIRS signals are necessary. This paper describes a reliable NIRS-based BMI system we have developed. The feasibility of the method was demonstrated through generating motion of a humanoid robot.

I. INTRODUCTION

Brain Machine Interfaces (BMIs) allow users to interact with devices through thought processes alone. BMIs or Brain computer Interfaces (BCIs) are mainly studied for patients who are suffering from severe motor impairments to interact or communicate with the external world. Recently, BMI applications to entertainment use such as controlling a humanoid robot are also proposed [1]. Expansion in application requires BMIs to become more simple and convenient.

BMIs detect changes in brain activity during specific mental tasks and output corresponding control commands to an external device. The development of BMI studies have been derived from improvement on technologies for recording brain activity. Since the BMI studies started, big achievements such as controlling robotic arm [2-5] were made by studies relied on invasive techniques for recording brain signals. Progress in non-invasive brain-imaging modality further pursued the BMI studies. Employing brain-imaging modalities, a variety of brain signals can be used by BMIs non-invasively. These include signals obtained by electroencephalographic (EEG), functional magnetic resonance imaging (fMRI), magnetoencephalo-graphy (MEG), positron emission tomography (PET), and near-infrared spectroscopy (NIRS) [6].

Although fMRI, MEG, and PET may provide good temporal resolution, they are only available under limited conditions. These modalities require bulky expensive equipment and therefore BMIs based on these techniques are impractical for widespread clinical and entertainment use. At present, EEG is the most practical modality for BMI. Only EEG has relatively short time constants, can function in most environments, and requires simple and inexpensive equipment [7]. There are numbers of recent demonstrations of EEG-based BMI for controlling robots [1, 8], wheelchairs [9, 10], and cursors on a computer screen for communication [11-13]. However, although existing studies showed the feasibility of EEG-based BMI, they have limitation in operation performance; only few control commands are available. One of the considerable approaches to increase the number of available control command is to use EEG in combination with other brain-imaging modalities.

NIRS is one of the most appropriate candidates for this approach. NIRS is a relatively novel optical brain-imaging technique and its application to BMI is actively proposed. Users of these BMIs perform tasks such
as motor tasks [14, 15] and motor imagery [16, 17] in order to control brain activation. BMI which detects the user’s subjective preference and utilize it as a control signal was also reported [18]. NIRS enables non-invasive, low-cost, and portable monitoring of brain activity. It measures changes in the brain’s hemodynamic response, while EEG measures electrical activity of neurons. Since measurement principles of these two modalities are different, NIRS-based BMI can utilize knowledge which EEG-based BMI have difficulties to utilize. EEG can only provide spatial information reconstructed by probabilistic models [19]. NIRS can provide spatial information more directly, and thus NIRS-based BMI can effectively utilize knowledge of cerebral localization. Existing NIRS studies showed results consistent with well-known findings about cerebral localization [20].

In order to prove the feasibility of NIRS-based BMI, inherent disadvantages of NIRS must be overcome. One major disadvantage of NIRS is instability of measurement. Its measurement values are relatively unstable compared to other functional imaging methods such as fMRI and MEG. In addition, NIRS-based BMIs need to overcome a disadvantage which is common to previous BMIs of all kinds. Most of existing BMIs require lengthy training periods, which can lead to frustration and anxiety on the part of the users [11-13, 17, 21-22].

In this paper, we have conducted experiments in order to improve the reliability of NIRS-based BMI by employing a method for detecting stable NIRS signals. The experimental results suggest that the differential signal of oxygenated hemoglobin levels in cerebral blood flow (CBF) recorded from two specific regions during mental arithmetic task is stable. Such NIRS signals can be detected without conducting any training to a subject. We have applied NIRS-based BMI system to humanoid robot control.

II. MATERIALS AND METHODS

A. Subjects
Seven healthy subjects (Four males and three females) participated in the experiment. All subjects were right-handed and had no neurological abnormalities. The subjects had never participated in prior BMI experiments and they didn’t have any previous knowledge about this experiment.

B. NIRS
We used an OMM-3000 NIRS system (Shimadzu Corporation). It consists of laser transmitter probes and laser receiver probes. Each transmitter probe emissions three different near-infrared laser beams. The wavelengths of three beams are 780±5, 805±5, and 830±5 nm. The lasers penetrate outer tissues of human head, pass through brain cortex, and are detected by receiver probes. NIRS system measures hemodynamic changes in the cortex which the lasers pass through.

![Diagram of NIRS system](image-url)
receiver probes were alternately placed in two rows and twelve columns. The space between a transmitter probe and a receiver probe was approximately 3 cm. The lower row was located on the line which connects T4, Fp2, Fp1 and T5 of the International 10-20 Electrode Placement System. Fig. 1 shows the allocation of the probes and recording channels. Recording channels are defined as regions between each pairs of transmitter probe and receiver probe. Subject’s hemodynamics were monitored by thirty four recording channels.

NIRS can assess two types of hemodynamic change associated with brain activity [23]. Neural activity is fueled by glucose metabolism. Increases in neural activity result in increased glucose and oxygen consumption, which leads to increase in deoxygenated hemoglobin (deoxy-Hb) concentration level. A reduction in local glucose and oxygen stimulates the brain to increase local CBF. Over a period of several seconds, the increased CBF carries oxygen to the area. The increased oxygen transported to the area typically exceeds the rate of oxygen consumption. An overabundance of cerebral blood oxygenation results in increase in oxygenated hemoglobin (oxy-Hb) and total hemoglobin (total-Hb) [23]. The initial increase in deoxy-Hb level, a phenomenon known as initial dip, occurs much faster than the changes in oxy-Hb and total-Hb levels. However, the signal of initial dip is weak and difficult to detect in real-time [24]. In this study, we have focused on increase in oxy-Hb which is pronounced and can be constantly monitored in real-time.

NIRS signals are sensitive to artifacts. The effects of artifacts can be classified into two general types. The first type is attributed to contact failure of receiver probes and scalp. Movement of subject can cause the receiver probes to lose contact with the scalp, exposing them to light which does not come out from the brain tissue. This type of artifact is relatively easy to filter out because it causes sudden, large, and recognizable spikes in the NIRS signals. The other type of artifact causes relatively slow and subtle changes in CBF. Changes in CBF can be caused by various elements other than voluntary mental tasks: subtle and inevitable head movements, involuntary physiological and psychological activities. These changes accumulate as time progresses. The accumulated changes in oxy-Hb level may become much larger than changes evoked by mental tasks and can be confused with the hemodynamic response due to the mental tasks.

Oxy-Hb level detected by NIRS is not an absolute value but a relative value to a baseline. In experimental situations, the baseline is defined as the average of oxy-Hb level during the latest rest period. In contrast, a baseline for BMI application can’t be defined in the same way since the timings of rest period are not predetermined. In actual use of BMI, the baseline is defined as oxy-Hb level at the time a user starts using it. Changes in CBF due to the artifacts accumulate as time progresses, which may result in confusing NIRS signals after a long term use.

![Image](https://example.com/image.png)
For BMI application, we employed differential signal of oxy-Hb levels recorded from two specific regions of subject’s brain. By subtracting one signal from the other, hemodynamic response common to widespread areas of brain may be balanced out and only changes specific to local remain. Local changes in CBF evoked by a mental task can be detected without being affected by widespread changes caused by artifacts even after a long term use. In this experiment, we examined if mental arithmetic task evokes such local changes to CBF.

C. Methods

In our preliminary experiments, easy arithmetic tasks such as multiplication with one-digit numbers and addition without carry didn’t evoke detectable changes in subject’s oxy-Hb level. In this experiment, we employed arithmetic tasks that are hard enough to excite brain activity.

<table>
<thead>
<tr>
<th>channel</th>
<th>Location of channel</th>
<th>Average value ± standard deviation (mM:mm:sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>F4</td>
<td>0.07±0.09</td>
</tr>
<tr>
<td>6</td>
<td>F5</td>
<td>0.16±0.18</td>
</tr>
<tr>
<td>7</td>
<td>F3</td>
<td>0.22±0.29</td>
</tr>
<tr>
<td>19</td>
<td>F7</td>
<td>0.41±0.15</td>
</tr>
<tr>
<td>25</td>
<td>T4</td>
<td>0.35±0.13</td>
</tr>
<tr>
<td>32</td>
<td>F7-T3</td>
<td>0.36±0.23</td>
</tr>
</tbody>
</table>

Each 30 seconds of a task period for solving computational problem was alternated by 60 seconds of a rest period for 4 repetitions. A couple of additions of three arrays of three-digit numbers such as “121+258+378” were shown on a
display in front of a subject during the task period. The subject kept on calculation until the task period ended. A cross symbol was shown on the center of the display during the rest period and the subject kept on watching it without thinking of anything. The Subject was not allowed to move over the entire experimental period. Changes in CBF were recorded by NIRS during the whole experiment.

III. RESULTS

A. Optical response

Fig. 2 shows the averages of all subjects’ oxy-Hb concentration level in time series. Subjects started mental arithmetic task at 0 second and stopped at 30 second. The values are relative values to baselines. The baselines are defined as averages of recorded oxy-Hb levels from -30 to -15 second. In Fig. 2, the number in each column shows corresponding recording channel number. The columns are put in the position corresponds to the location of the recording channel on the surface of the subjects’ head, which is shown in Fig. 1. Bilateral frontal cortices and bilateral temporal lobes show significant activations during mental arithmetic task while prefrontal cortex didn’t show remarkable change. This result is confirmed by a previous research which measured hemodynamic changes by fMRI during arithmetic tasks [25]. In the research, contribution of working memory to solving arithmetic problems is analyzed. With NIRS, the activity of working memory can be detected by the channel located near F7 of the International 10-20 Electrode Placement System (Fig. 1). Table I shows average channel on F7 during each rest and task trial (hF 7). As standard deviation of time integral of oxy-Hb levels from 0 to 30 second with the recording channel number and shown in the graph, ranges of hF 7 during both rest and its position in the 10-20 system. It can be said that oxy-Hb levels recorded by channels on temporal region (ch 19, 25, 32) changed more significantly than those recorded by task period are unstable. This is assumed to be caused by artifacts which gradually change the amount of CBF and its oxy-Hb level. channels on forehead (ch 5, 6, 7). In Fig. 3, discriminative Fig. 4 (b) shows ranges of the difference between hF 7 and hF 4 during both rest and task. The oxy-Hb concentration level measured by ch 32 located between F7 and hF 4 during each rest and task trial. In Fig. 4 (b), the T3 increased remarkably during the task compared to values hF 7 – hF 4 during both rest and task.
periods fall the level measured by ch-5 located near F4 within a certain range. The maximum difference between B. Stable NIRS signal for BMI. hF 7 and hF 4 during task period is constantly larger than 5 sec moving average of oxy-Hb level recorded by the maximum during rest period. BMI system performs channel on X is represented as hX in this article. This is stable discrimination of the brain activity during rest and done to take into account sudden artifacts caused by sensor contact failure. Fig. 4 (a) shows a typical subject’s range of 5 sec moving average of oxy-Hb level recorded by the task by the threshold determined by the first several trials, which is shown in Fig. 4 (b).

IV. SPELLERS BASED ON SSVEP

In a BCI based on Steady-State Visual Evoked Potentials (SSVEP), the system reflects the user attention to an oscillating visual stimulus [41]. Flicker-VALIDATION

In a BCI based on Steady-State Visual Evoked Potentials (SSVEP), the system reflects the user attention to an oscillating visual stimulus. Flickering lights at different frequencies are usually used as stimuli. Their responses appear in the visual cortex and correspond to SSVEP at the same frequencies and higher harmonics [31]. The amplitude and the phase that define an SSVEP response depend on the frequency, intensity and the structure of the repetitive visual pattern [45]. SSVEP based BCIs have been used in many types of applications like for neuroprosthetic devices control, for the restoration of the grasp function in spinal cord injured persons [30] and video games [25]. Indeed, this type of BCI performs very well and is reliable according to previous studies [5, 10, 19, 18]. While each cell of the matrix can correspond directly to a command in the P300-Speller, the low number of commands of an SSVEP-BCI involves an adaptive strategy for creating the graphical user interface. Among the different laboratories working on SSVEP-BCI, the Institute of Automation in Bremen, Germany has proposed several efficient SSVEP-Spellers.
The SSVEP based Bremen-BCI speller has been evaluated during the CeBIT fair 2008 in Hannover, Germany and RehaCare 2008 in Duesseldorf, Germany [3, 13, 39, 43]. The graphical user interface of Bremen-BCI speller is presented in Fig. 3. This interface is composed of a virtual keyboard with 32 characters (letters and special symbols), which is located in the middle of the screen. The five white boxes at outer edges and upper left corner of the screen are flickering with different frequencies. These boxes correspond to the commands “left”, “right”, “up”, “down”, and “select”. The subject does not need to shift his gaze too much, because the used stimuli are part of the GUI on the same LCD screen. This setup, as opposed to having an LCD for the GUI and a separate LED board for the visual stimuli, is much more convenient for the user as they do not have to shift their gaze too much.

In the command level, i.e., the five commands, the mean accuracy of the command detection is 92.84%, with an average information transfer rate of 22.6bpm. In the speller level, the average information transfer rate is 17.4bpm, equivalent to about 3.5cpm.

The SSVEP speller developed by Cecotti [9] (CBCI) is a recent SSVEP-Speller that does not need any calibration step. Thus, this speller is ready to work once the subject is prepared. This speller was also developed at the Institute of Automation in Bremen, Germany. The visual stimuli are here fully integrated to the graphical user interface (GUI). Contrary to some other SSVEP-BCIs, the visual stimuli and the commands are merged. This speller allows writing 27 characters: the 26 Latin characters [A..Z] and Ş for separating the words. CBCI is depicted in Fig. 4. This interface corresponds to a menu with three possible choices. When a choice is selected, then the content of this choice is split into three new choices. Three commands are dedicated to the navigation. They correspond to the three boxes that contain all the possible letters. For writing a letter, the user has to produce three commands. This number of command is fixed and independent of the letter. One command is considered for canceling the previous one. An easy access to the “undo” command must be present for enabling easily a fast correction from the user. An error can come from the user directly or indirectly. This command aims at minimizing the cost of a mistake during spelling tasks. A command is dedicated to the deletion of the last character in the written text. At any moment, the user is able to suppress the last character of the text with only one command.

CBCI was tested on eight healthy subjects. The average accuracy and information transfer rate are 92.25% and 37.62bpm, which is translated in the speller with an average speed of 5.51cpm. One subject could write with an average speed of 7.34cpm.

V. SPELLERS BASED ON MOTOR IMAGERY

Like for SSVEP-BCIs, the number of available commands limits the interface: it is not possible to assign an imagery movement to every character. A strategy must be found to combine few basic BCI commands, e.g., thinking to moving the left/right hand. A predictive BCI speller based on motor imagery has been proposed at AIRLab, the Artificial Intelligence and Robotics Laboratory at the Department of Electronics and Information of the Politecnico di Milano, the Technical University of Milan, Italy [15]. The GUI of this speller is presented in Fig. 5. The selection strategy is based on target expansions, like a menu, with 27 available characters,
numbers, symbols. This speller possesses a predictive capabilities: it allows word suggestions and disabled improbable symbols.

The achieved performance are relevant. With one subject, they have obtained a high classification accuracy and the overall speller speed is estimated to 3cpm. With two other subjects, they started with lower classification accuracies, but significant improvements have been achieved with more training sessions. These subjects reached a spelling speed of respectively 2 and 2.7cpm [15].

The BCI research group from the Fraunhofer FIRST (IDA), Berlin, Germany has proposed the Berlin BCI (BBCI) called Hex-o-Spell [8, 29]. This asynchronous BCI speller allows to write 29 different characters and the backspace command. The speller is controlled by two mental states: imagined right hand movement and imagined right foot movement. Six hexagonal fields are surrounding a circle. In each field, five characters or other symbols like backspace are arranged. An arrow is placed in the center of the circle for the selection of a character. When the subject imagines a right hand movement, the arrow turns clockwise. With an imagined foot movement, the rotation stops and the arrow starts extending to the desired field. Once the field is selected, the six fields are arranged with the content of the selected field. The BBCI has been tested in real condition on two volunteer and healthy subjects during the CeBIT fair 2006 in Hannover, Germany. The speed of the hex-o-spell BCI was between 2.3 and 5cpm for one subject and between 4.6 and 7.6cpm for the other one. This speed was measured for error-free, completed sentences, i.e., all typing errors that have been committed had to be corrected by using the backspace of the mental typewriter. This protocol was also used to evaluate CBCI. The original and efficient Hex-o-spell interface has also recently been tested with the visual oddball paradigm [38].
In spite of the different results reported in the literature, it is not possible to have an objective comparison between the different available BCI spellers due to the inter-subject variabilities and the conditions of the experiments. For instance, the experimental conditions are very different between a dedicated EEG room in a laboratory and a booth at an international fair with all the surrounding noise. However, each BCI paradigm possesses its advantage and drawbacks. BCIs based on the detection of the P300 or SSVEP require external visual stimuli. For spelling applications, the visual stimuli are not really a disadvantage. Indeed, spellers based on motor imagery consider also a graphical user interface. With the P300 speller, each symbol is usually available on the screen, like a classical virtual keyboard. Contrary to the P300 speller, an SSVEP speller must take into account several constraints based on the visual stimuli. With LEDs, it is possible to produce a large number of visual stimuli with different frequencies [19, 46]. However, such oscillation requires an external device; the application and the visual stimuli are not located at the same place. With visual stimuli on an LCD screen, the size, the low luminosity, the vertical refresh rate of the screen are some parameters that limit the number of simultaneous visual stimuli on the screen. For this reason, it is not possible to propose the user a virtual keyboard with a direct access to the letters. Other BCI commands shall be used to navigate on the virtual keyboard. For an efficient BCI, the performance shall be reliable over time and across subjects. BCIs based on motor imagery, like the Hex-o-spell, can be efficient. However, BCIs based on motor imagery or P300 requires a training session for the calibration of the system. In addition, BCIs based on motor imagery suffer of BCI illiteracy; the performance is highly dependent of the subject. On the other hand, SSVEP-BCIs do not require a training session and possess a high transfer rate [5, 9]. A low BCI performance can be due to a lack of attention, to the disrespect of what should be written. It is possible that the user wants to produce a command but the signal processing module delivers the wrong command. In this case, the error is not voluntary and shall be corrected easily. At any moment, the user should be able to cancel the previous command with only one command.

VII. CONCLUSION

Communication through spelling is still one of the main challenge in BCI applications. Writing a simple message, an e-mail,... remains a difficult task to achieve for people with severe disabilities. The BCI literature has exponentially increased in the past few years. Whereas recent BCI competitions have allowed to compare different machine learning methods, these benchmarks are limited to one aspect of a BCI. The graphical user interface should actually benefit the same attention than the signal processing part [2]. This is particularly the case with SSVEP spellers that have constraints due to the number of available flashes on the screen. The presented spellers in this paper are only based on one type of brain activity. The next generation of BCIs will combine the detection of several brain responses, as hybrid BCIs [32]. Such oscillation could provide faster and more robust spellers. They could solve to some extent the BCI illiteracy. This problem can be determinant for the choice of a specific BCI. Recent works have been conducted to address this problem: for P300 [21, 20], SSVEP [3], and sensorimotor rhythms [42]. Further work should be carried out in the comparison of different well known and proven BCI systems with the same set of subjects. The different materials (amplifiers, caps,...) could be an obstacle for comparing and sharing BCIs. Hopefully, well established and promising BCI frame-works like BCI2000 and OpenViBE could allow a better comparison between spellers [35, 34].

ACKNOWLEDGMENT

This work has been supported by a Marie Curie European Transfer of Knowledge grant BrainRobot, MTKD-CT-2004-014211, within the 6th European Community Framework Program, and by French National Research Agency (ANR) through TecSan pro- gram (project RoBtK ANR-09-TECS-013).

REFERENCES


[38] M. Treder and B. Blankertz. (c)over attention and visual speller design in an erp-based brain-computer interface. Behavioral and Brain Functions, 6(28), 2010.


