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Design of differential Near-Infrared Spectroscopy based Brain Machine Interface

H. Matsuyama, H. Asama, and M. Otake

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), magnetoencephalography (MEG), positron emission tomography (PET), and near-infrared spectroscopy (NIRS) [6].

Although fMRI, MEG, and PET may provide good spatial and 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

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H. M., H. A., and M. O. Authors are with the Research into Artifacts, Center for Engineering, 5-1-5 Kashiwa-no-ha, Kashiwa City, Chiba Japan (phone: 0471-36-4248; fax: 0471-36-4248; e-mail: {matsuyama, asama,, otake}@race.u-tokyo.ac.jp).

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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.

Twelve transmitter probes and twelve receiver probes were used in this experiment. Transmitter probes and 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.

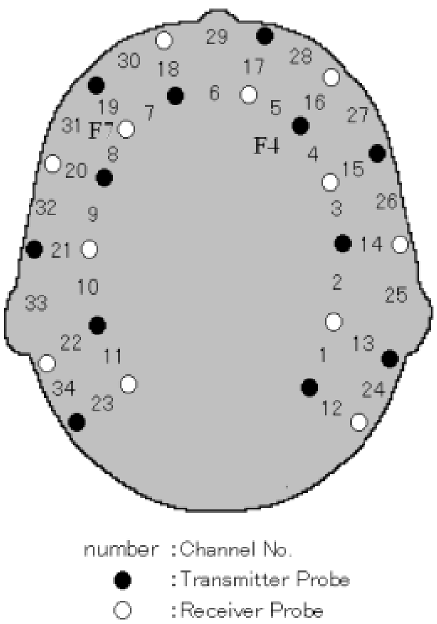

Fig. 1. Allocation of NIRS transmitter probes, receiver probes and recording channels on the surface of a subject's head. Suffixed alphabets represent positions in International 10-20 Electrode Placement System

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

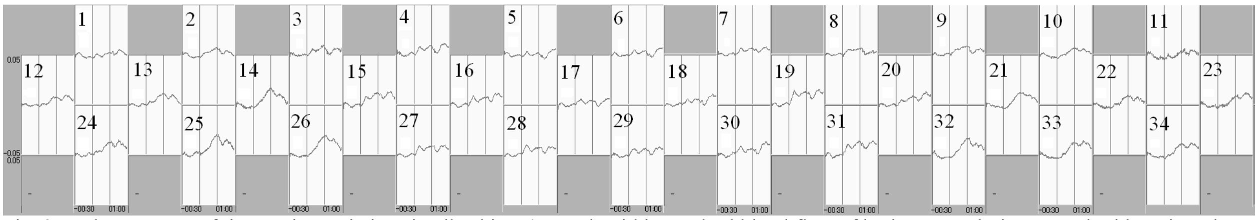

Fig. 2. The averages of time series variations in all subjects' oxyHb within cerebral blood flow of brain cortex during mental arithmetic tasks. The number on each column corresponds to the number on Fig. 1.

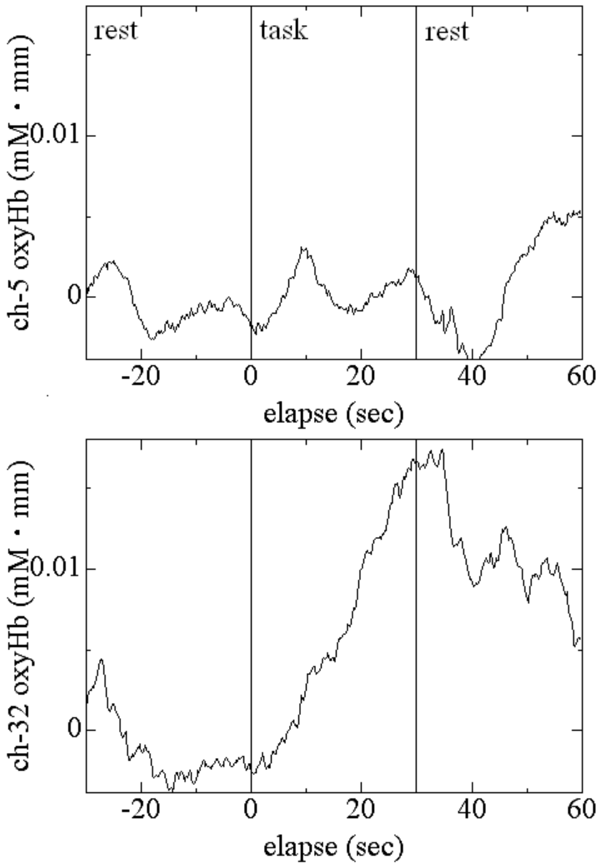

Fig. 3. The averages of time series variations in all subjects' oxyHb measured by ch-5 (F4) and ch-32 (F7).

confusing NIRS signals after a long term use.

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.

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.

TABLE I
AVERAGE VALUE AND STANDARD DEVIATION OF OXYGENATED HEMOGLOBIN.

channel	location of channel	time integral of oxyHb level average ± standard deviation (mM・mm・sec)
5	F4	0.07±0.09
6	Fz	0.16±0.18
7	F3	0.22±0.29
19	F7	0.41±0.15
25	T4	0.35±0.13
32	F7-T3	0.36±0.23

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,

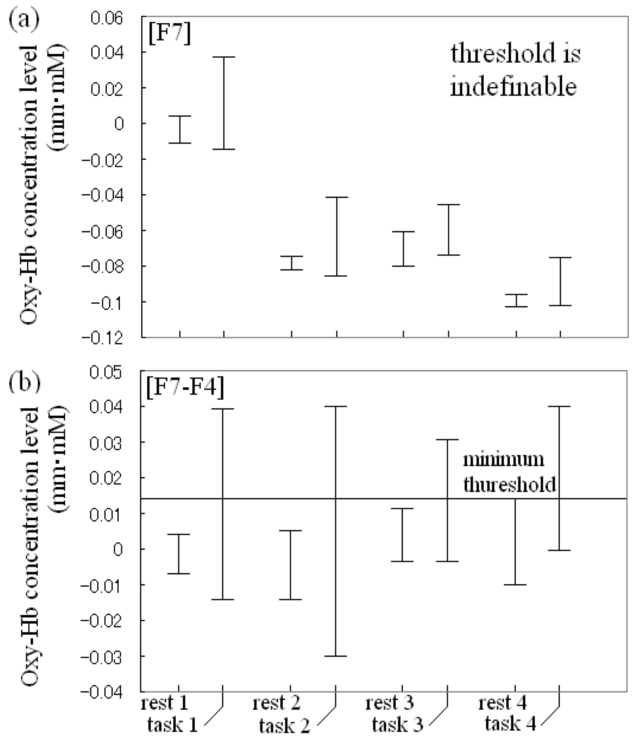

Fig. 4. A typical subject's oxyHb level ranges during each rest and task trial at F7 (a) and F7-F4 (b). The data shown in the figure is 5 sec moving average.

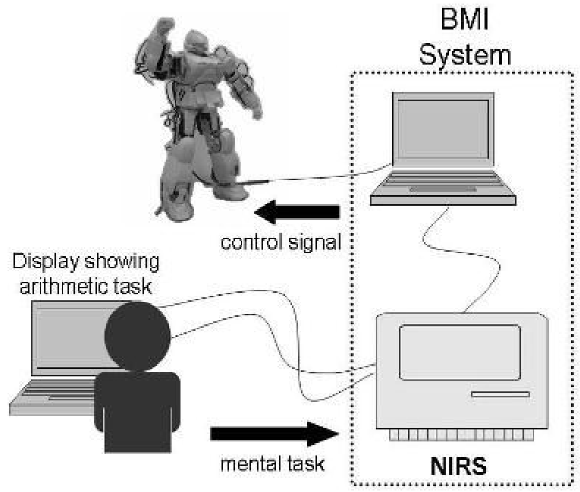

Fig. 5. The setup of NIRS-based BMI consisting of NIRS device, a computer for analyzing NIRS signals, and a display for showing arithmetic tasks.

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 and standard deviation of time integral of oxy-Hb levels from 0 to 30 second with the recording channel number 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 channels on forehead (ch-5, 6, 7). In Fig. 3, discriminative channels are selected from Fig. 2. The oxy-Hb concentration level measured by ch-32 located between F7 and T3 increased remarkably during the task compared to the level measured by ch-5 located near F4.

B. Stable NIRS signal for BMI

5 sec moving average of oxy-Hb level recoded by channel on X is represented as h_X in this article. This is 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 channel on F7 during each rest and task trial (h_{F7}).As shown in the graph, ranges of h_{F7} during both rest and task period are unstable. This is assumed to be caused by artifacts which gradually change the amount of CBF and its oxy-Hb level.

Fig. 4 (b) shows ranges of the difference between h_{F7} and h_{F4} during each rest and task trial. In Fig. 4 (b), the values $h_{F7} - h_{F4}$ during both rest and task periods fall within a certain range. The maximum difference between h_{F7} and h_{F4} during task period is constantly larger than the maximum during rest period. BMI system performs stable discrimination of the brain activity during rest and task by the threshold determined by the first several trials, which is shown in Fig. 4 (b).

TABLE II
MINIMUM THRESHOLD AND RESPONDING TIME OF NIRS-BASED BMI TO EACH SUBJECT'S INTENTIONS.

Subject ID	Minimum threshold (mM·mm)	Average of minimum responding time (sec)
1	0.00671	9.1
2	0.00606	7.9
3	0.00963	6.5
4	0.00791	4.0
5	0.00697	17.1
6	0.0271	7.2
7	0.00652	11.9

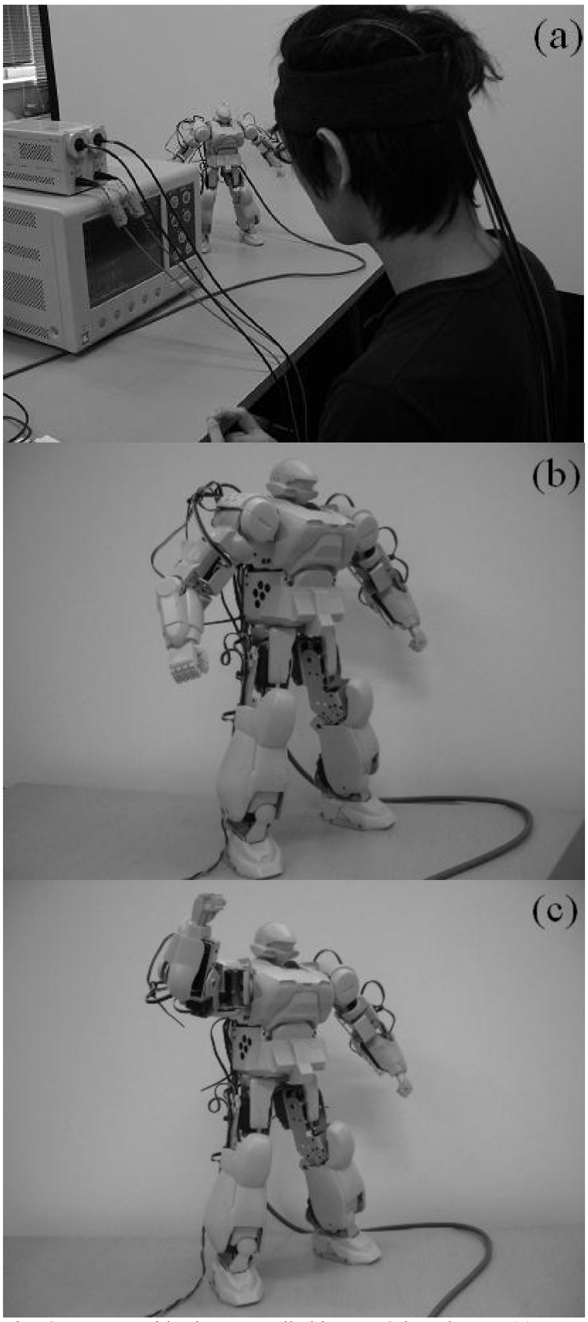

Fig. 6. Humanoid robot controlled by NIRS-based BMI: (a) BMI sends control signals to the robot. (b) When inequality (1) is false, the arms of the robot are down. (c) When inequality (1) is ture, the right arm is raised

IV. BMI SYSTEM

NIRS-based BMI system consists of a NIRS device (NIRO-300, Hamamatsu Photonics Corporation), a computer for analyzing NIRS signals, and a display for showing arithmetic tasks. BMI system is connected to a General Robotix HRP-2m humanoid robot (Fig. 5). The arithmetic tasks on the monitor will be updated in after a certain period of time. Users solve arithmetic tasks on the

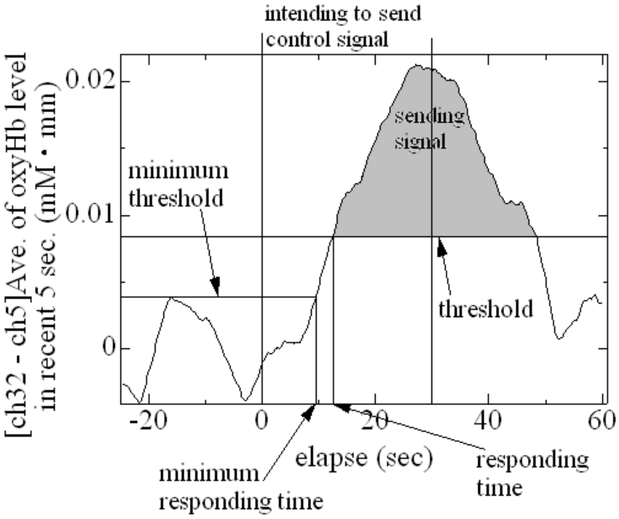

Fig. 7. The responding time of BMI depends on the level of the threshold.

timing when they intend to produce a control signal. Recording channels of NIRS are located on F4 and F7.

BMI sends control signal to the robot constantly while inequality (1) is true. Invariable T is the threshold.

$$(h_{F7} - h_{F4}) - T > 0 \qquad (1)$$

The minimum threshold is the highest value during the all rest periods as shown in Fig. 4 (b). The threshold should be set at level higher than the minimum threshold in order to prevent unintended transmission of control signal.

The minimum thresholds for all of seven subjects calibrated from the result of experiment are shown on Table II. The NIRS-based BMI was customized for each subject.

BMI system transmits control signals to the robot to raise right arm (Fig. 6(a)). When inequality (1) is false, both of the arms are down (Fig. 6(b)). When inequality (1) is true, right arm of the robot is raised (Fig. 6(c)).

V. DISCUSSION

NIRS-based BMI system we have developed can serve as stable controller of a robot. Since arithmetic task is an everyday task for most of people, and since our system detects hemodynamic response to such an everyday task, users can use NIRS-based BMI system without training. However, this system has limitation in responding times. The responding time is elapsed time from the moment a user intended to send control signal until the difference between h_{F7} and h_{F4} become larger than threshold (Fig. 7). The minimum threshold and the average of minimum responding time of all seven subjects are listed on Table II. The delay of control signal ranges from a few second to over ten second. Users may sense significant delay from the moment they intended to control devices.

The delay is due to slowness of hemodynamic changes in oxy-Hb concentration level. In order to improve the response of NIRS-based BMI, we need to employ quicker hemodynamic response, such as initial dip, as a trigger of a control signal.

VI. CONCLUSION

In this study, we proposed and developed NIRS-based BMI system. In order to overcome existing problems on NIRS that its measured raw data are unstable, we employed differential signals of oxy-Hb concentration levels during mental arithmetic task as input to BMI system. Thresholds were calibrated through the first several trials for each subject so as not the users to be trained for adapting to the system. The input is proved to be stable and can be evoked without trainings. Future work includes diminishing the responding time of NIRS-based BMI to make it more user-friendly interface.

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