2011年中国自动化大会
暨钱学森诞辰100周年
和五十周年会庆纪念
2011 Chinese Automation Congress
2011年11月26日-11月29日 中国·北京
A Multichannel fNIRS Based Brain Computer Interface System Using Speed and Force Imagination

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Abstract—In this paper, we present a Brain Computer Interface (BCI) system using multichannel functional near-infrared spectroscopy (fNIRS) signal acquired when subjects execute speed and force imagination of right hand. Our goal is to classify much more movement imagination details so that a BCI system can provide more control commands, which is helpful for BCI application. Six subjects (3 male, 3 female) participate in the experiment for 3 sessions. We use Gaussian filter and wavelet-MDL to preprocess the acquired signal, and then use support vector machine (SVM) to classify task state versus rest state and speed imagination versus force imagination. Our results show that using oxyhemoglobin (HbO) data as feature can get comparable results with a BCI system.

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ICI has got great development in recent years. Many modalities can be used to measure brain activities, such as electroencephalography (EEG), electrocorticography (ECoG), positron emission tomography (PET), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and functional near infrared spectroscopy (fNIRS)[1-3]. Currently, most BCI systems use EEG as the signal to decode the users’ thought, because EEG has advantages of high temporal resolution, low hardware cost, and less technically demanding. However, EEG signals are prone to movement artifacts. Also, the fixation of EEG electrodes is time costing, and the spatial resolution is low. These disadvantages require users to train a lot to use an EEG based BCI system.

fNIRS is a technology to measure deoxyhemoglobin (Hb) and oxyhemoglobin (HbO) concentration changes caused by brain activities using near-infrared light. Hb and HbO have high absorption ability for light that has wavelength lower than 650nm. On the other side, water absorbs much more light when the wavelength higher than 950nm. These properties make an optical window between wavelength 650nm and 950nm possible to emit light into the human brain and detect the output light at centimeters away. The modified Beer-lambert law is used to determine the Hb and HbO concentration changes using the detected light intensity changes[4].

Figure 1. Optical window in human tissue (molar extinction coefficient data of Hb and HbO from [5], and extinction data of water from [6]).

During mental activation, oxygen-rich blood will inrush to the active area and surrounding tissue, causing increase in HbO and decrease in Hb[4]. These features make fundamental for fNIRS-based BCI. Though this response appears several seconds after the activation, the property of high spatial resolution makes fNIRS an advantage to set up a BCI system.

Currently, few researches have been done to build an fNIRS-based BCI system [7-9]. Most motor imaginary paradigms used for both EEG and fNIRS based BCI systems are movement of different limbs, such as left hand, right hand, foot, tongue, or other hand movements. However, such
paradigms cannot provide enough commands to control a complex device smoothly. In this paper, we proposed a paradigm to use speed and force imagination of the same hand (right hand) to distinguish movement type imagination. Thus we can get more control commands when using both hand imaginations. Our goal is to control a robot fluently using movement imaginary based BCI.

II. EXPERIMENT

The architecture of an fNIRS-based BCI system is shown in figure 2. Near infrared light transmits through the scalp, the skull, the cerebrospinal fluid and reach the cerebral cortex. Hb and HbO concentration changes due to cognitive activities in brain impact on the absorption of the incident light, and by detecting the output light intensity the concentration changes can be calculated. Preprocessing methods are used to eliminate high frequency noise and low frequency tendency. Then the preprocessed data are used as feature to classify which imagination the user is executing, and the classification results are transformed to commands to control a robot. The user changes his imagination type depending on the feedback of the robot.

A. Experiment Paradigm

Each trial of the experiment consists of four parts (Figure 3): base time (10s), cue time (2s), task time (10s) and rest time (10-12s). During the cue time, subjects are instructed which imaginary to execute. Taking into consideration of different clenched force and speed types, each task is divided into 3 subtasks. For clenched force imaginary, we first measure the right hand maximum force (MF) of each subject, and then request them to clenched actually at 20%, 50% and 80% of the maximum force respectively. When they participate in the experiment, they just imagine the feeling of real clenched force, not actually do those. For clenched speed imaginary, we instruct the subjects to clenched their right hand at three different frequencies: 0.5Hz, 1Hz, and 2Hz. To our knowledge, 2Hz clenched speed is nearly the fastest speed one can get.

B. Subjects

6 subjects participate in the experiment, 3 male and 3 female. Their average age is 26.8 years. Among them, 3 subjects are well trained, and the other 3 just simply instructed, as described in table 1. All of them are healthy and have no neurological or psychiatric history or on medication. They also give written informed consent for the experiment. The experiment was approved by the Ethical Committee of the Shenyang Institute of Automation, Chinese Academy of Science, China.

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C. Data Acquisition

We use ETG-4000 (a multichannel fNIRS instrument, Hitachi Medical Corporation) to acquire Hb and HbO data during motor imaginary. To measure the activation area of cerebral cortex, two sets of 3 × 3 optode are selected. The optode has 10 illuminators and 8 detectors. Each illuminator emits near-infrared light at two wavelengths: 695nm and 830nm. The area between an illuminator and a detector is a measurement channel. C3 and C4 in 10-20 system are used to locate the optode (Figure 4).
Every subject takes part in 3 acquisition sessions. Each session contains 60 trials, which are 30 trials for every imaginary task (10 trials for every imaginary subtask). The sample frequency is 10Hz.

III. METHODS

A. Preliminary Signal Processing

We use NIRS-SPM to do preliminary signal processing for the data [10]. Based on SPM5 and MATLAB, NIRS-SPM is a software package for statistical analysis of near-infrared spectroscopy (NIRS) signals.

The first work during this process is converting the optical density data acquired by ETG-4000 to Hb, HbO and HbT concentration change signals. The original concentration data contains many high frequency noise caused by heart beat or head muscle activities, low frequency noise due to breath, unknown reason Mayer-wave, vaso-motion or other experimental errors (Figure 5).

Then, we use Gaussian Filter (Full Width at Half Maximum (FWHM) = 1.5s, a parameter for Gaussian Filter) to low pass the original concentration signal and remove the unknown global trends caused by cardiac, breathing, vaso-motion, or other experimental errors by wavelet – minimum description length (MDL) detrending algorithm[11]. The processed concentration signal and its power spectral density can be seen in Figure 6.

B. Feature Selection

Related studies show that when local cortex area is activated, HbO concentration changes much bigger than Hb. In this paper, we use HbO data and Hb-HbO combined data from all the 24 channels respectively as the classification feature (Figure 7). Comparing the classification results, we can determine which kind of feature is more suitable for our research.

C. Pattern Classification

We applied Support Vector Machine (SVM) to the classification problem. SVM is a popular machine learning method for classification, regression and other learning tasks [12]. Unlike other classification methods that reduce the dimension of feature space, SVM maps the original finite-dimensional space into a higher or even infinite-dimensional space. Doing this can make the classification problem easier, as data sets that cannot be linearly separated in lower dimensional space can be separated in higher dimensional space. A kernel function K(x, y) is used to fulfill the mapping process, and a training algorithm is used to maximize the margin between the training patterns and the decision boundary[13].

We use libSVM to implement the SVM classifier [14]. This is an integrated software package for support vector classification, regression and distribution estimation. It also
supports multi-class classification. To classify the Hb and HbO concentration change patterns, we first transform the datasets into LibSVM format, then scale the data and choose radial basis function (RBF) as the kernel function. After doing this we use 5 fold cross-validation to identify good parameters so that the classifier can accurately predict unknown data. Finally, the best parameters are used to train the whole training set and get the prediction model.

Subjects implemented 60 trials in one session. The trial number is too small to get stable classification accuracy. So, we adopt the 5 fold cross – validation accuracy to evaluate the classification results[15]. When we use 5 fold cross-validation, the training dataset is randomly divided into 5 subsets of equal size. Sequentially 4 subsets are used to train the classifier and the 1 left is used to validate the classifier. In this way every instance in the training set is predicted, and the cross-validation accuracy is more stable to verify the percentage of the correctly classified data. This technology can prevent over-fitting problem and get a more reasonable result.

IV. RESULTS

A. Classification Results with HbO Feature

To control a robot with fNIRS based BCI, the first factor we concern is whether the system can separate task (motor imaginary) state from rest state. When using HbO signal 10s before and after imagination task onset from all the 24 channels as feature, the classification accuracy of 4 subjects is more than 80%, including subject 2 as high as 96.11% (Figure 8). The other 2 subjects who are simple trained have accuracy rate about 64%. Taken into consideration of training effects, well trained subjects (1, 2, and 6) have mean accuracy of 86.98%, and simple trained subjects (3, 4, and 5) have mean accuracy of 69.63% (Figure 9).

B. HbO Feature versus Hb & HbO Feature

Using HbO as feature, we can get an acceptable result. Early research shows when local cortex is activated, HbO concentration will increase, and Hb concentration will decrease at the same time. This means that Hb can also provide some feature during motor imaginary. Then we use Hb & HbO as feature and the classification results are shown in Figure 12 and 13. The compare of the two kinds feature implies that Hb can not provide additional distribution for classification of both task versus rest and speed versus force.
C. Left Head versus Right Head versus Whole Head

In the experiment, both speed and force imagination are of right hand. To identify whether left head area dominates the classification, we compare the results using HbO feature of left head, right head and whole head (Figure 14). For well trained subjects, classification accuracy using feature from left head area is better than from right head area. Also, the result is comparable to using feature from whole head area. However, compare of simple trained subjects shows no obvious difference.

D. Classification Results with Different Feature Periods

The main drawback using an fNIRS based BCI is the time lag due to the nature of vascular response to neural activities. So we examine the feature period effects on classification results. Doing this can help us control a robot more naturally. For example, when controlling a mobile robot, we can give it a not very precise command at the beginning of its movement, and adjust the action with a more and more precise command during time progress.

The classification accuracy using different feature period is shown in Figure 15 and 16. For classification between task and rest, both well trained and simple trained subjects get more precise accuracy when feature period increase. At feature period of 3.5s, well trained subjects can get 73.52% accuracy, and simple trained subjects 59.91% accuracy. For classification between speed and force imagination, accuracy of well trained subjects increase after 6s feature period, but accuracy of simple trained subjects shows no increase.

V. CONCLUSIONS

In this paper, we preset an fNIRS based BCI system. This system uses speed and force imagination of right hand to produce command for controlling a robot. Doing this can provide more precise command for the real application of BCI systems. Though fNIRS has less temporal resolution than EEG, its high spatial resolution property, as well as other advantages such as low cost, less prone to movement, non-invasive and non-ionization makes it ideal for BCI application.

Our results show that using feature of HbO concentration changes can get the same accuracy comparing to feature of Hb & HbO combined concentration changes. This means that HbO concentration changes can provide enough information for classification of mental state. Although fNIRS has advantage of high spatial resolution, our research show that appropriate training is essential to get a high classification results. At the same time, the results imply that though left head area dominate classification results during right hand movement imagination, right head area also provide enough information for a reasonable classification. Also, the research about effects of feature period on classification accuracy demonstrates that some key points exist to provide critical features for classification.
Future work include: finding other features such as frequency characteristics of HbO concentration changes for classification; classifying imagination type details such as the speed parameters and force parameters; acquiring brain signal using both fNIRS and EEG together, as well as an online BCI system. Our goal is to provide much more movement imagination parameters for BCI system, and finally use the system to control a robot smoothly.

ACKNOWLEDGMENT

We give thanks to all the subjects participated in the experiment.

REFERENCES