Classification of fNIRS Data Using Wavelets and Support Vector Machine during Speed and Force Imagination

Baolei Xu, Yunfa Fu, Lei Miao, Zhidong Wang, Hongyi Li

Abstract—In this paper, we present a method for classifying functional near-infrared spectroscopy (fNIRS) data using wavelets and support vector machine (SVM). fNIRS data is acquired by ETG-4000 during speed and force imagination. Probes location is around C3 and C4 in 10-20 international system. After preprocessing the data using NIRS-SPM, we decompose it with ‘db5’ wavelet for 9 levels to do a multiresolution analysis (MRA). Then, the approximation and detail signal at every level are used for SVM classification using libSVM toolbox. The results show that frequency band between 0.02 and 0.08Hz is important for classification, especially frequency band between 0.02 and 0.04Hz. This finding is useful for building an fNIRS-based brain computer interface (BCI) system.

I. INTRODUCTION

FUNCTIONAL near infrared spectroscopy (fNIRS) is a new tool to study hemodynamic response during brain activities [1]. Currently, this method has been widely used in disease monitoring [2], cognitive research [3, 4], and brain activity imaging [5, 6]. The technology measures brain activities in optical manner, offering a different aspect to explore the nature of brain function from electroencephalography (EEG), electrocorticography (ECoG), positron emission tomography (PET), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI). Additionally, this approach has better spatial resolution than EEG, and is less cost comparing to MEG, PET and fMRI. These advantages make fNIRS a potential modality to be used in BCI [7-11].

In 2006, Muroga, et al. used a neural network to quantitatively estimate start and end timing of tapping movement [12]. Coyle, et al. developed a straightforward custom-built fNIRS-BCI system in 2007, and achieved ‘on/off’ switching using mean hemodynamic response levels [13]. Sitaram, et al. classified left-hand and right-hand motor imagery using SVM and Hidden Markov Model (HMM), taking preprocessed oxyhemoglobin (HbO) and deoxyhemoglobin (Hb) data from all the channels as feature [14]. However, few researches has been done to find out which frequency band is better for imagination type classification, and we want to explore this problem to some extent.

In the following text, we will demonstrate the architecture of an fNIRS-based BCI system and discuss the key issues that influence its application. Then, we will show a method to classify fNIRS data using wavelets and SVM. The data is acquired when subjects do speed and force imagination of right hand using ETG-4000. We choose 24 probe channels around C3 and C4 in 10-20 international system because our analysis shows that both channels around C3 and C4 carry information about right hand imagination. NIRS-SPM is used to do preliminary preprocessing for the data. After that, we use ‘db5’ wavelet to decompose the preprocessed data for 9 levels, and use libSVM toolbox to classify the approximation signal and detail signal at every level. Our results exhibit that frequency band between 0.02 and 0.08Hz is significant for classification, especially between 0.02 and 0.04Hz. We only do off-line analysis in this paper, as it is essential for us to build an online BCI system.

II. FNIRS-BASED BCI SYSTEMS

The fact that Hb and HbO response to subject’s brain activation makes an fNIRS based BCI system possible. The main issue to evaluate a BCI system is information transfer rate. The nature that hemodynamic response lags behind neural activities leads to disadvantage for the usage of fNIRS. However, the modality has better spatial resolution than EEG, which may contribute to high classification accuracy.

Another problem in most current noninvasive BCI system is that different limb movement imagination is used. This bring to a consequences that we can only get few control command to control an outside device. To solve this dilemma, we import movement parameters imagination. In our paradigm, we use clenches speed and clenches force imagination of the same right hand. Doing this can equip us with more imagination states and control commands to control a robot more conveniently.

Our fNIRS-based BCI system consists of four parts (Fig. 1):
the fNIRS data acquisition block, the intention classification block, the action block and the user. With successful classification between task state and rest state, the user can control the robot whether to move or not. With classification between speed and force imagination, the user can control robot what movement to do.

To get such target, we design an offline experiment to testify whether we can classify task state from rest state, as well as clench speed imagination from clench force imagination. Unlike Coyle [13] and Sitaram [14] who use preprocessed Hb and HbO signal as feature, we employ wavelets to decompose the preprocessed signal, and use the approximation signal and detail signal of hemodynamic response as feature to do classification. Our results show that this method can get a better classification results.

III. DATA ACQUISITION FOR SPEED AND FORCE IMAGINATION

Six subjects take part in the experiment, including three male and three female. Their average age is 26.8 years. They are divided into two groups. One group is well trained and the other group is simply trained, as described in Table 1. Well trained subjects are trained more than 3 times (at least one hour per time) before the experiment, including two of them have previous EEG acquisition experience, and simple trained subjects are only simply instructed once one day before the experiment. None of them are in disease or have neurological or psychiatric history. All of them give written informed consent to participate in the experiment. The experiment is approved by the Ethnical Committee of the Shenyang Institute of Automation (SIA), Chinese Academy of Science (CAS), China.

| TABLE I | SUBJECT DETAILS |
|---------|-----------------|
| Number  | 1 2 3 4 5 6     |
| Gender  | Female Female Male Male Female Male |
| Age     | 28 33 25 24 26 25 |
| Training| Well Well Simple Simple Simple Well |

A. Experiment Paradigm

Most experiment paradigms used in BCI use imagination of different limb movements, such as left hand movement, right hand movement, foot movement, even tongue movement. The drawback of such paradigms is less command for BCI, which affects information transfer rate of the system. So, we use speed and force imagination of right hand as task in our experiment, which is useful to get more control command, as well as imagination details. Taking into consideration of different clench force and speed types, each imagination is subdivided into three sub-types: 20%, 50%, 80% of maximum clench force (MF), and 0.5Hz, 1Hz, 2Hz of clench speed. Subjects do different types of clench force actually according to hand dynamometers and remember the feeling. The feeling is recalled when they do different clench force imagination. Again, clench speed imagination is implemented by actual practice according to metronome first and recall the feeling when doing clench speed imagination.

A single trial of the experiment consists of four periods, as shown in Fig. 2: ten seconds baseline period, two seconds cue periods, ten seconds task period, and ten to twelve seconds rest period. All the subjects participated in 3 sessions. Every session contains sixty trials, including thirty trials for clench force imagination and thirty trials for clench speed imagination.

B. Data Acquisition

We use ETG-4000 (Hitachi Medical Corporation) to acquired Hb and HbO response when brain is activated by clench speed and force imagination. To measure the cerebral cortex area activated by movement imagination, two sets of 3 × 3 optodes are selected and placed around C3 and C4 in 10-20 international system, as shown in Fig. 3. The optodes have 10 illuminators and 8 detectors. Illuminators emit near-infrared light at two different wavelengths: 695nm and 830nm.

Fig. 1. Block diagram of an fNIRS based BCI System

Fig. 2. Experiment paradigm

Fig. 3. fNIRS optodes arrangement
IV. FNIRS DATA CLASSIFICATION

The original Hb and HbO data acquired by ETG-4000 is firstly preprocessed by NIRS-SPM [15] to remove high frequency noise using Gaussian filter and to remove global trends caused by heart beat, breathing, and vaso-motion using wavelet-MLD (minimum description length) detrending algorithm [16]. Then, the preprocessed data is decomposed by ‘db5’ wavelets and classified by SVM.

A. Wavelet Decomposition

The wavelet transform is different from the Fourier transform. In Fourier transform, signals are represented as a sum of sinusoids, from which we can get no time information of the signal analyzed. Though Short-time Fourier transform (STFT) is time and frequency localized, but there exists frequency/time resolution trade-off. Using multiresolution analysis (MRA) [17], wavelets often give a better signal representation with balanced resolution at any time and frequency.

In our research, we choose ‘db5’ wavelet to do a 9 level multiresolution analysis using MATLAB. As described in Fig. 4, the original signal is divided into multiple approximation components \((c_A)\) and detail components \((c_D)\):

\[
signal = c_{A_1} + c_{D_1} = c_{A_2} + c_{D_2} + c_{D_1} = c_{A_3} + c_{D_3} + c_{D_2} + \cdots + c_{D_1} = c_{A_9} + c_{D_9} + c_{D_8} + \cdots c_{D_2} + c_{D_1}
\]

The sample frequency we use when acquiring fNIRS data is 10Hz, so the highest frequency in the original signal is 5Hz. In our experiment paradigm, the duration time of a whole trial is 32~34s, which is corresponding to about 0.03Hz. This guides us to do the multiresolution analysis up to 9 levels to get the least frequency band of 0 ~ 0.01Hz. The combination of Hb and HbO signal from all the channels at every approximation and detail level are used as classification feature.

B. SVM classification

SVM is a popular machine learning method that can be used for classification, regression and other learning tasks [18]. Other classification methods reduce the dimension of feature space, while SVM maps the original finite-dimensional space into a higher or even infinite-dimensional space. Data sets that cannot be linearly separated in lower dimensional space can be separated in higher dimensional space. So, SVM can make the classification problem easier. To fulfill the mapping process, a kernel function \(K(x, y)\) is used. Then, a training algorithm is used to maximize the margin between the training patterns and the decision boundary [19].

We choose libSVM toolbox to implement the SVM classification [20]. This toolbox supports SVM classification, regression, distribution estimation, as well as multi-class classification. When using it, we first transform the datasets into libSVM format, scale the data, and select radial basis function (RBF) as kernel function. Then, 5-fold cross-validation is used to identify good parameters and finally, the prediction model can be got by training the whole training set using the best parameters. We use 5-fold cross-validation accuracy to evaluate the classification results, because the 60 trials got in one session is too small to get stable classification accuracy [21]. By doing this we can also prevent over-fitting problem.

| Type          | c_{A_1}  | c_{A_2}  | c_{A_3}  | c_{A_4}  | c_{A_5}  | c_{A_6}  | c_{A_7}  | c_{A_8}  | c_{A_9}  |
|--------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Well trained | Mean     | 92.7%    | 92.7%    | 92.7%    | 92.6%    | 92.9%    | 92.3%    | 92.1%    | 47.3%    | 47.3%    |
|              | Std      | 5.2%     | 5.2%     | 5.2%     | 4.9%     | 4.9%     | 3.2%     | 2.8%     | 1.4%     | 0.8%     |
| Simple trained | Mean   | 66.8%    | 66.8%    | 66.8%    | 66.7%    | 67.0%    | 69.6%    | 67.3%    | 46.8%    | 46.4%    |
|              | Std      | 13.4%    | 13.4%    | 13.4%    | 13.2%    | 12.9%    | 13.6%    | 18.5%    | 1.3%     | 1.0%     |

| Type          | c_{D_1}  | c_{D_2}  | c_{D_3}  | c_{D_4}  | c_{D_5}  | c_{D_6}  | c_{D_7}  | c_{D_8}  | c_{D_9}  |
|--------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Well trained | Mean     | 57.0%    | 55.5%    | 58.8%    | 60.7%    | 61.7%    | 60.5%    | 91.6%    | 99.1%    | 49.5%    |
|              | Std      | 7.2%     | 2.2%     | 5.1%     | 5.1%     | 6.3%     | 3.7%     | 3.3%     | 0.4%     | 1.4%     |
| Simple trained | Mean | 59.9%    | 56.9%    | 56.2%    | 58.7%    | 57.6%    | 51.8%    | 75.0%    | 86.6%    | 49.8%    |
|              | Std      | 3.2%     | 1.9%     | 2.5%     | 3.0%     | 5.0%     | 2.5%     | 8.9%     | 8.6%     | 1.0%     |
TABLE IV
CLASSIFICATION RESULTS OF SPEED VS FORCE, WITH FEATURE CONSISTS OF APPROXIMATION SIGNALS AT LEVEL 1 TO 9

| Type           | cA_1  | cA_2  | cA_3  | cA_4  | cA_5  | cA_6  | cA_7  | cA_8  | cA_9  |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Well trained   | Mean  | 72.2% | 72.2% | 72.2% | 72.4% | 71.7% | 68.9% | 67.4% | 67.4% | 61.1% |
|                | Std   | 5.4%  | 5.4%  | 5.4%  | 5.2%  | 4.8%  | 4.2%  | 5.7%  | 3.2%  | 2.9%  |
| Simple trained | Mean  | 61.3% | 61.3% | 61.3% | 61.3% | 60.9% | 59.1% | 59.4% | 60.6% | 55.9% |
|                | Std   | 4.7%  | 4.7%  | 4.7%  | 4.7%  | 5.0%  | 6.1%  | 4.7%  | 2.0%  | 0.3%  |

TABLE V
CLASSIFICATION RESULTS OF SPEED VS FORCE, WITH FEATURE CONSISTS OF DETAIL SIGNALS AT LEVEL 1 TO 9

| Type           | cD_1  | cD_2  | cD_3  | cD_4  | cD_5  | cD_6  | cD_7  | cD_8  | cD_9  |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Well trained   | Mean  | 60.6% | 55.4% | 57.8% | 59.1% | 56.3% | 64.1% | 68.7% | 66.1% | 58.9% |
|                | Std   | 4.4%  | 2.3%  | 2.9%  | 2.6%  | 0.3%  | 2.1%  | 3.1%  | 7.1%  | 1.1%  |
| Simple trained | Mean  | 57.6% | 57.4% | 60.9% | 57.4% | 56.5% | 60.0% | 60.2% | 55.4% | 62.2% |
|                | Std   | 5.3%  | 3.1%  | 2.8%  | 3.1%  | 0.9%  | 1.9%  | 4.2%  | 2.0%  | 0.6%  |

Fig. 5. Classification results of task vs rest for well trained subjects using (a) approximation signal and (b) detail signal at every level

Fig. 6. Classification results of task vs rest for simply trained subjects using (a) approximation signal and (b) detail signal at every level

Fig. 7. Classification results of speed vs force for well trained subjects using (a) approximation signal and (b) detail signal at every level

Fig. 8. Classification results of speed vs force for simply trained subjects using (a) approximation signal and (b) detail signal at every level
V. EXPERIMENT RESULTS

In our research, the classification problem is divided into two parts. The first part is classification between task state and rest state (Table II, III). By doing this we can get the information whether the subject is doing some imagination task. The other part is classification between clench speed imagination and clench force imagination (Table IV, V). By doing this we can distinguish which imagination the subject is doing and use the information to control outside devices.

A. Classification between Task and Rest States

The classification results between task state and rest state is shown in Table II and Table III using approximation signal and detail signal of preprocessed Hb and HbO response as feature respectively. We divided the results into well trained subjects and simply trained subjects because training condition can affect the results significantly. By doing this we can better explain our results.

From the single-sided amplitude spectrum of the preprocessed Hb and HbO signal (Fig. 9), we infer that classification results from approximation and detail level 1 to 4 changes little. But the classification results show that detail level 7 and 8 (corresponding to frequency band 0.02 to 0.04Hz) contains significant information for classification, especially detail level 8 (corresponding to frequency band 0.02 to 0.04Hz). For well trained subjects, classification accuracy increases to as high as 99% (Fig. 5). Even for simple trained subjects, classification accuracy increases to 87% (Fig. 6). These results are better than using original preprocessed signal whose accuracy results are 92% and 67% for well trained and simply trained subjects respectively.

![Fig. 9. Single-sided amplitude spectrum of preprocessed signal](image)

B. Classification between Speed and Force

The classification results between clench speed and clench force imagination is different from results between task state and rest state. Frequency band between 0.02 and 0.08 Hz differentiate task state from rest state. This condition applies to the variance between speed and force imagination for well trained subjects to some extent, but not for simply trained subjects. More frequency bands seem to contribute to clench speed and clench force imagination.

VI. CONCLUSIONS AND DISCUSSIONS

In this paper, we introduce a method to classify fNIRS data during brain activation using wavelet MRA and SVM. The classification results indicate that the main variance between task state and rest state is frequency band between 0.02 to 0.08Hz, especially between 0.02 to 0.04Hz. Using detail signal for classification between task state and rest state, we can get accuracy of 99% for well trained subjects and 87% for simple trained subjects, while accuracy is 92% and 67% for well trained and simple trained subjects respectively using original preprocessed Hb and HbO signal. In our experiment paradigm, a single trial’s period is 32s to 34s, which corresponding to 0.03Hz. This may contribute to the results on a certain degree.

The variance between clench speed and clench force imagination is different from variance between task state and rest state. Although we can get some good results at some frequency band (69% for well trained subjects, and 62% for simple trained subjects), but the results is less good than use all frequency bands (72% for well trained subjects, and 61 for simple trained subjects). This implies that more frequency bands affect the classification between clench speed and clench force imagination.

Currently, we only study the frequency band difference during brain activation. We are sure that there exists some spatial pattern that influences classification results. Also, in our experiment we use different imagination of the same hand, and get some good results. The results will be better when using imagination of different hand. Thus we can distinguish more brain state to control a robot conveniently.

Before decomposing fNIRS data with wavelets, we preprocess it with Gaussian filter and wavelet-MDL. This leads to frequency loose at high frequency band, which may contains some useful information. We will explore whether high frequency band contains useful information and try other preprocess methods that utilizes the information to help increase the classification accuracy. Currently we are developing a customized multichannel fNIRS system, and using it we can acquire hemodynamic response at higher sample rate to study high frequency band useful for classification.

The main drawback for fNIRS to be used in BCI system is its time lag. This is the nature of hemodynamic response to neural activities and we can not change it. However, if this modality can provide much precise classification, whether in single use or in joint use with EEG, in addition with fast optical signal [22], fNIRS will become a good option for building a reliable BCI system.
In this paper, we only do some off-line analysis of fNIRS data, which is essential for building an on-line fNIRS-based BCI system. Our future work includes identifying other features such as spatial feature for classification, and building an online fNIRS-based based BCI system. Also, we have done an experiment to acquiring EEG and fNIRS data simultaneously when subjects doing imagination task. Developing algorithm to classifying with EEG and fNIRS data together is also one important work in this research. Our final goal is to build an on-line BCI system using EEG and fNIRS simultaneously, and make the system work with high speed and high accuracy.

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