Comparison of optical and concentration feature used for fNIRS-based BCI system using HMM

XU Baolei12,a, Fu Yunfa3,b, Shi Gang1,c, Yin Xuxian12,d, Miao Lei1,e, Wang Zhidong1,f, Li Hongyi15,g

1State Key Laboratory of Robotics, Shenyang Institute of Automation (SIA), Chinese Academy of Sciences (CAS), Shenyang 110016, P. R. China
2University of Chinese Academy of Sciences, Beijing 100049, P. R. China
3School of Automation and Information Engineering, Kunming University of Science and Technology, Kunming 650500, P. R. China
4Dept. of Advanced Robotics, Chiba Institute of Technology, Chiba 2750016, Japan
5School of Mechanical Engineering & Automation, Northeastern University, Shenyang, China

ablxu@sia.cn, bfyf@ynu.edu.cn, csg0105@sia.cn, dyinxuxian@sia.cn, emiaolei@sia.cn, fzhidong.wang@it-chiba.ac.jp, ghli@sia.cn

Keywords: Brain-Computer Interface (BCI), functional Near-Infrared Spectroscopy (fNIRS), Hidden Markov Model (HMM), feature selection.

Abstract. Brain-Computer Interface (BCI) is very useful for people who lose limb control such as amyotrophic lateral sclerosis (ALS) patients, stroke patients and patients with prosthetic limbs. Among all the brain signal acquisition devices, functional near-infrared spectroscopy (fNIRS) is an efficient approach to detect hemodynamic responses correlated with brain activities using optical method, and its spatial resolution is much higher than EEG. In this paper, we investigate the classification performance of both optical signal and hemodynamic signal that both used in fNIRS-based BCI system using Hidden Markov Model (HMM). Our results show that hemodynamic signal has a much lower error rate than optical signal, especially the Oxy-hemoglobin (HbO) has the lowest error rate. This result is important for researchers who want to design an fNIRS-based BCI system and get better performance.

Introduction

Brain-Computer Interface (BCI) is a technology to control an outside device using brain signals directly, which is especially important for people who lose limb control such as amyotrophic lateral sclerosis (ALS) patients, stroke patients and patients with prosthetic limbs. The concept of BCI was first funded by America Defense Advanced Research Projects Agency (DARPA) in 1970s [1], and get great development since 1990s [2]. Currently, there are more than 300 institutions doing BCI related researches. Its applications include rehabilitation [3], games control [4], virtual environment [5], robot control [6], car control [7], prosthetics control [8], wheel chair control [9] and military weapon control [10].

The brain signal used for BCI control can be acquired noninvasively from many equipments, such as electroencephalograph (EEG) [11], magnetoencephalography (MEG) [12], functional magnetic resonance imaging (fMRI) [13], and functional near-infrared spectroscopy (fNIRS) [14]. The EEG is the most used method because its high sampling frequency, small size and low cost compared with MEG and fMRI. However, the spatial resolution of EEG is very low due to the capacitance resistance effect of cerebro-spinal fluid and the skull. Fortunately, fNIRS provides another way to investigate brain activities through hemodynamics approach with higher spatial resolution than EEG [15]. Furthermore, the signals acquired by fNIRS is highly related to fMRI signals [16], but the price of fNIRS equipment is an order lesser than fMRI.
fNIRS technology employs near-infrared light at two or more wavelengths to detect the Deoxy-hemoglobin (Hb) and Oxy-hemoglobin (HbO) concentration changes in the brain cortex using the modified Beer-Lambert Law [15]. Both the optical signal [17, 18] and concentration signal [19, 20] can be used for BCI control. However, no paper has compared the performance difference between optical signal and concentration signal when they are used for BCI classification. In this paper, we investigate this problem using motor imagery paradigm and hidden Markov model (HMM). Our results show that HbO signal can get the lowest classification error rate, and HbO should be paid higher priority in fNIRS-based BCI system.

Experiment Design

**Experiment Paradigm.** In our experiment, we use clench force and clench speed motor imagery of right hand as the paradigm, which is an effective way to improve BCI control commands. Six subjects participate in the experiment, including three well trained subjects and three no trained subjects to explore training effects on classification results. All of them give their written approval to join the experiment, and the experiment is approved by the Ethical Committee of the Shenyang Institute of Automation (SIA), Chinese Academy of Sciences (CAS).

The experiment is divided into three sessions, and each session contains 60 trials, including 30 trials of clench force motor imagery and 30 trials of clench speed motor imagery. Taken into consideration of the intrinsic time lag of hemodynamic response to brain activities, the task period of each trial lasts 10s, following by 20s rest time to decrease the hemodynamic response to base level. Twenty-four fNIRS channels cover the cortical motor area around C3 and C4 in 10-20 international system are used to get the maximum hemodynamic response to motor imagery.

**Data acquisition.** The fNIRS data is acquired by ETG-4000 produced by Hitachi Co., Limited. There are two types of probe to measure the hemodynamic response. One type is the light emitter, which emits near infra-red light at wavelength of 695nm and 830nm. The light is shined into the brain tissue and scattered to the surface of the brain at centimeters away, and received by the probe of light detector. The received optical intensity signal of two wavelengths are used to calculate the hemodynamic signal of Hb and HbO using the modified Beer-Lambert Law.

Data Process Methods

**Preprocess Methods.** The original optical signal and the concentration signal calculated by the modified Beer-Lambert Law contains low frequency linear drift due to the change of connection strength between the probes and the subject’s brain surface, as is shown in the left part of Fig.1. So, we preprocess the signals using linear detrend first. The right part of Fig.1 is the time course of the linear detrended signal and its corresponding power spectrum calculated using Welch’s method after removing the DC component. It is clear that both optical signal and concentration signal contain heart beat rhythm and its high order harmonic waves. The power spectrum of optical signal looks like that of concentration signal because the latter one is calculated by the Beer-Lambert Law, as is shown in Eq. 1, where DPF is the ratio of optical photon’s actual path length and the distance between the light source and the detector, and $\epsilon_{\lambda_1/Hb}/\epsilon_{\lambda_2/HbO}$ is the extinction coefficient of Hb/HbO under the corresponding wavelength [21]. The useful signal used for fNIRS is under 0.1Hz [14], so we need to remove high frequency noise using a low pass IIR filter of Chebyshev II at cutoff frequency of 0.1Hz.

$$
\Delta C = \begin{pmatrix}
\Delta C_{Hb} \\
\Delta C_{HbO}
\end{pmatrix} = \begin{pmatrix}
\epsilon_{\lambda_1/Hb} & \epsilon_{\lambda_1/HbO} \\
\epsilon_{\lambda_2/Hb} & \epsilon_{\lambda_2/HbO}
\end{pmatrix}^{-1} \begin{pmatrix}
\log \left( \frac{I_{\lambda_1}(t)}{I_{\lambda_2}(t)} \right) \\
\log \left( \frac{I_{\lambda_1}(t)}{I_{\lambda_2}(t)} \right)
\end{pmatrix} \begin{pmatrix}
DPF_{\lambda_1} \\
DPF_{\lambda_2}
\end{pmatrix} \begin{pmatrix}d \\
d\end{pmatrix}
$$  (1)
Hidden Markov Model. Hidden Markov Model (HMM) is a statistical Markov model in which only the outcome of the model can be observed and the states are not visible to the observer [22]. The model changes its hidden states according to the transition probability matrix, and the observation of a state changes according to the associated probability distribution. HMM is widely used in applications such as speed recognition, activity recognition, gene finding, protein sequence alignment, and other sequence classification related areas [23]. A discrete HMM in which the output observations are discrete can be described by \( \lambda = (N, M, \pi, A, B) \), where \( N \) is the number of hidden states, \( M \) is the number of observations, \( \pi \) is the initial hidden state distribution, \( A \) is the transition probability matrix of hidden states, and \( B \) is the probability distribution in each of the observations. Generally there are three main problems in HMM: the evaluation problem, the decoding problem, and the learning problem. The first problem is to get the probability of a sequence \( O = o_1, o_2, \cdots, o_T \) produced by a given model \( \lambda \), and this problem is usually solved by the forward-backward algorithm. The middle problem is to calculate the most likely hidden state sequence \( Q^* = q_1^*, q_2^*, \cdots, q_T^* \) given the observation sequence \( O \) and the model \( \lambda \), which can be solved by the Viterbi algorithm. The last problem is to calculate the model \( \lambda \) from a given observation sequence \( O \) which can maximize \( P(O | \lambda) \), and this problem can be solved by the Baum-Welch algorithm.

Feature Selection. In this paper, we use the signal amplitude as classification feature. As is shown in Fig.2, the signal amplitude course of clench force motor imagery is different from that of clench speed motor imagery. As HMM is efficient for time sequence classification, the amplitude from 0s to 12s is selected as the input vector. To decrease feature dimensions, we down-sampled the signal to 1Hz. As we have low-pass filtered the signal at 0.1Hz, the down sampling process will not lose any information according to Shannon’s sampling theorem. Also, to decrease the feature dimensions, we only select one channel around C3 in feature space. Feature space with more channels will be studied in the future work.

Classification. In our research, we design two HMM models with observation probabilities of continuous multivariate Gaussian distribution for force imagery and speed imagery respectively, because the feature vectors are continuous variables. The observation probability distribution can be described as Eq. 2, where \( N(X, \mu_{jk}, \Sigma_{jk}) \) is the multivariate Gaussian distribution, \( \mu_{jk} \) is the mean vector, \( \Sigma_{jk} \) is the variance matrix, \( K \) is the number of Gaussian distribution contained in \( b_j(X) \), and \( c_{jk} \) is the combination coefficient that constrained to \( \sum_{k=1}^{K} c_{jk} = 1 \).

\[
b_j(X) = \sum_{k=1}^{K} c_{jk} b_j(X) = \sum_{k=1}^{K} c_{jk} N(X, \mu_{jk}, \Sigma_{jk}) , \quad 1 \leq j \leq N
\]  

(2)
The Baum-Welch algorithm used for continuous HMM model learning is the same with that for discrete HMM model, except that the probability distribution $B$ is modified using Eq. 3–5, where

$$
\gamma_t(j, k) = \sum_{i=1}^{N} a_{t-1}(i) a_{j} b_{jk}(O_{t}) \beta_{t}(j) / P(O / \lambda).
$$

The details of the algorithm can be found in [22].

The classification results between force imagery and speed imagery for the four feature types are evaluated using 5-fold cross-validation to make the results more accurate using pm4tk3 [24].

Results

The classification results to distinguish clench force motor imagery from clench speed motor imagery are shown in Fig. 3. As the subjects participated in the experiment are divided into well trained ones and no trained ones, we investigate the results respectively. For all the subjects, the error rate using HbO as feature is lower than that using 695nm optical signal as feature at a significant level of 0.01. For well trained subjects, the HbO feature has lower error rate than 695nm and 830nm at a significant level of 0.01. For no trained subjects, there is no significant difference between the HbO feature and other features. These results imply that HbO is the best signal for fNIRS-based BCI system.
Table 1 The significant level of rejection the null hypothesis that the error rate of HbO is smaller than other signals

<table>
<thead>
<tr>
<th>Signal Type</th>
<th>Hb 695nm</th>
<th>830nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>well trained subjects</td>
<td>0.25</td>
<td>0.01*</td>
</tr>
<tr>
<td>no trained subjects</td>
<td>0.3</td>
<td>0.25</td>
</tr>
<tr>
<td>all subjects</td>
<td>0.15</td>
<td>0.01*</td>
</tr>
</tbody>
</table>

Fig.3 Classification results for 4 different feature types (the left one is the error rate for all 6 subjects, the middle one is the error rate for 3 well trained subjects, and the right one is the error rate for 3 no trained subjects)

Discussions and Conclusions
fNIRS is a booming approach for BCI applications. It uses optical approach to measure the hemodynamic response related to brain activities, and both optical signal and the concentration signal can be used for classification of different motor imagery tasks. In this paper, we investigate the performance of different feature types, and find that HbO is the best signal type for BCI application. This result is very useful for researchers who want to build a BCI system using fNIRS equipment and get better results. Currently, we only use one single channel to distinguish the clench force imagery and clench speed imagery of the same hand, and get an error rate of 38% for well trained subjects. The classification rate is lower than the results of distinguishing from different limbs such as distinguishing left hand imagery from right hand imagery. However, the idea of distinguishing motor imagery parameters is useful to increase BCI commands, which is important for BCI systems in real applications. We are sure that more accurate result will be get when more channels are included in the feature space in our future work.

Acknowledgement
This work is supported by the National High Technology Research and Development Program of China (863 Program) under Grant No. 2012AA02A605, and National Natural Science Foundation (NNSF) of China under Grant No. 61203368, 61102014 and 61005069.

References


