Channel Selection with EEG Source Imaging

Ming-ai Li*, Chun-ting ZHANG and Yan-jun SUN

Faculty of Information Technology, Beijing University of Technology, Beijing 100124, China

*Corresponding author

Keywords: EEG, Channel selection, EEG source imaging, Motor imagery, Wavelet transform.

Abstract. Brain computer interface (BCI) is a technology recording brain signals and translate into machine language to drive device movement. To improve the convenience and practicability of BCI systems, it is necessary to reduce the number of channels of EEG without reducing classification accuracy. In this paper, a channel selection method was proposed. Combine continuous wavelet transform (CWT) with EEG source imaging (ESI), we can find out the source distribution of two kinds of motor imagery (MI) tasks on the cortex. Then the different value of source distribution on the cortex was projected to scalp. The value on the scalp was treated as a criterion for channel selection. While ESI was applied for locating the active areas, we can not only find out the prior channels clearly, but also figure out the expected areas briefly. The satisfying results show that the combination of CWT and ESI is a potential method for dealing with MI tasks.

Introduction

For those people suffering from motor disabilities but being cognitively intact, BCI technology has provided an optional method to communication with the environment. On account of the low cost and high resolution, EEG is becoming the most popular brain signal in Clinical application and scientific research [1]. To achieve a productive EEG classification performance, most EEG-based BCIs acquire multiple signals of electrodes on the scalp [2,3]. However, different recorded signals at different scalp will not provide the same discriminatory information [4], a large number of channels will bring noisy and excrescent information which bring down the performance of BCI [5,6]. In addition, numerous channels will lead to a time-consuming performance that affects the convenience in the use of the BCI. It would be inconvenient for clinical device widely used with a mass of channels. Thus a moderate number of channels will balance the required accuracy and the needs for performance and convenience.

Various methods have been proposed for channel selection [8,9]. Fisher discriminant analysis was introduced to find out the desired channels for right hand and right foot classification based on time segment and channel positions [7], the results provided to be effective in reducing training time with a rare decrease of classification performance. CSP-rank was proposed to reduce the number of channels [10]. In each filter, the absolute value of the filter coefficients were sorted and searched the largest coefficient by turn from two spatial filters. This method removed those channels with low contribution for classification and the high accuracy confirmed the feasibility of MI classified into two class in the range of electrodes. However, the previous research concentrated on the signals obtain scalp, analyzed the difference of each channel and found out the features of a series of channels between two kinds of MI [7,8,9,10]. Although the signals were produced in the cortex, few studies pay attention to the source distribution.

In order to translate scalp-recorded signals into cortex space, the EEG inverse problem was introduced. The source analysis methods, which are used to analysis brain signals in source spaces and translate noninvasively recorded scalp signals into physical regions, are potential methods for us to explore the inner workings of the brain[11]. Taking advantage of source analysis methods such as equivalent dipole model and cortical imaging technique are thought to be potential methods for classifying MI tasks in BCI systems. The superiority of those inverse methods is that reconstructed source distributions could be treated as a substitution representation of scalp recordings, make up for the distortion and blurs effect created by volume conduction effect.
For ESI technique, numbers of scholars have made in-depth studies. Low-Resolution electromagnetic tomography (LORETA) [12] was first proposed by R.D. Pascual-Marqui, which applied into two different sets of evoked potential data, the result provided to be physiologically meaningful but in many solutions unsuccessful. Then R.D. Pascual-Marqui came up with another method named standard low-resolution electromagnetic tomography (sLORETA) [13] with zero location error. Brad Edelman[11] used weighted minimum norm estimate (WMNE) to search out the optimal source distribution; the results showed that four-class classification of right hand tasks by using EEG source imaging approach were able to improve nearly 10% compared with traditional technology. Xu et al. proposed NEtwork based SOurce Imaging (NESOI) method [14]. Compared with other methods, NESOI was a potentially useful method for EEG source imaging without the use of Functional Magnetic Resonance Imaging (fMRI) priors. With the help of source analysis methods, we can figure out cortex distribution as the reflection of the real cortex distribution.

In this paper, we proposed an ESI-based method for channel selection. For all tasks, the same kind of trials strung together and continuous wavelet transform (CWT) was used for further analysis. The mean of wavelet coefficients of two MI in particular frequency band were analysed by ESI and the source distribution on the cortex were generated respectively. Then the different values of source distribution on the cortex were projected into scalp. The top value of the channel on the scalp was regarded as the optimal channel. This paper is organized as follows: experimental data and the preprocessing procedure were shown in section 2, channel selection method was illustrated in section 3, experimental results were presented in section 4.

Data Description and Preprocessing

The EEG data used in this study is from BCI competition III dataset IVa, provided by Fraunhofer FIRST (Intelligent Data Analysis Group) and Campus Benjamin Franklin of the Charite-University Medicine Berlin (Neurophysics Group) [15], with two classes: right hand and right foot MIIs. On account of using 128 channel Ag/AgCL electrode cap and 118 EEG channels were recorded at position of the extended international 10/20-system, this dataset is appropriate to us for channels selection. During the experiment, with the reminder visual cues, each experiment lasted for 3.5s, with a resting time between two trials was randomized from 1.75 to 2.25 seconds. Each class of EEG signals consists of 140 trials. The signal recorded was band-pass filtered between 0.05-200HZ, and digitized at 1000HZ.

Research show that while imaging movements of different body parts, the phenomenon of event-related desynchronization (ERD) and event-related synchronization (ERS), causing the power attenuation or enhancement in relevant cortex areas[16]. While imaging right hand movement, the energy of right hand representation area in the left brain will increase, however, a foot movement would lead to the ERS phenomenon in right hand representation areas of both sides of the brain [17]. Based on the phenomenon of ERD/ERS, we can figure out different body parts of MI, which turn the MI BCI feasible. By this way, the EEG data we used that were downsampled at 100 Hz from 1000HZ, and band-pass filtered to the 8–32 Hz frequency band by FIR filters. This band contains the Mu (8-12HZ) and Beta (18-25HZ) rhythms which have been reported to desynchronize in the MI task [24]. These neurological phenomena have been provided to be successful in the application of BCI systems to classify EEG signals.

Channel Selection Method

Continuous Wavelet Transform

In order to figure out the major channels on the scalp, we should find out the cortex areas distribution first. Since the number of dipoles are large, we should keep those areas with strong correlation and weaken those with no connection of MI activities. CWT was used to figure out the time window and frequency band in this paper, which divided the signals into frequency band with time-varying and clearly display the distribution of power in time and frequency domain. In the
present study, the signals of each channel were calculated by complex Morlet’s wavelets approach. The same kind of imaginations strung together. Then the mean of wavelet coefficients from 8-30Hz for all 118 channels of two MI tasks were extracted for further work.

ESI for Channel Selection

NESOI [21] is used for solving EEG source imaging problem in this paper. Three-sphere head model was used and the lead-field matrix was figured out for canonical mesh by Fieldtrip software [22]. In this research, each mesh was regarded as a dipole, which include 8196 dipoles with uniform distribution on the cortex.

With the help of NESOI, we could found the most obvious activity areas on the cortex. The top values on the cortex of different MIs are identified as dipole locations and included in the region of interest (ROI). In order to convert data from source domain to sensor domain, an EEG based model was provided to describe the scalp value and source activity. The selected topography was mapped onto 118 channels on the scalp through Equation (1), where A presented the lead field and X the source activities, b presented the scalp value. The channels with top values were regarded as the major channels.

\[ b = AX \]  

(1)

Experiment Result

Feature Mapping

The selected channels of data set “aa” “al” “av” “aw” “ay” ranked using EEG source imaging method are presented in this paper. The source distribution is shown in Fig. 1. Most subjects review the similar phenomenon in the left representation areas on the cortex (“aa” “al” “aw” “ay”) except one (“av”). The selected ROI position, which distribute on the surface of the cortex, turn to be distinct for each subject. For major subjects (“aa” “al” “ay”), the selected ROI are mainly spread around the similar areas but not absolutely uniform, which lead to the selected channels various. It is worth noticing that “aw” shows a special result, both left representation areas and right representation areas emerge strong in ROI, because the ERD phenomenon is strong in those areas and ERS occur robust in the opposite side of the areas (“aw”).

Figure 1. Source distribution of five subjects.
The selected channels distribution (only top ten channels are presented) are shown in Fig. 2. Most subjects have the adjacent channels (“aa” “al” “ay”) which proved to be hypothetical for further analysis. Subjects “aa” “al” “ay” share the same channels of CCP5, CCP3, CP5, CP3, PCP3 while subjects “al” “av” “aw” provide the channels on both side of the brain.

Classification result

CSP was used for feature extraction and SVM for classification in this paper. The classification rates are shown in Fig. 3 and the selected channels number are from 2 to 30. As shown Fig. 3, subjects “aa” and “ay” have the similar performance in classification result, five top channels perform perfect action and the accuracy keep steady above 90%. For all subjects, ten channels are sufficient enough to present all channels for classification without a significant reduction in accuracy.

Figure 2. Selected ten channels distribution of five subjects.

Figure 3. Classification of different selected channels of five subjects.

To carry out a further analysis, two methods named fisher discriminant and CSP-rank are introduced to confirm the feasibility of channels selection in this paper. The recognition accuracies
are shown in Table 1. Compared with fisher discriminant and CSP-rank, ESI manifests a high accuracy for subject “al” and “ay”. ESI perform better than CSP-rank in subject “aa” and Fisher discriminant in subject “av”. However, it is regrettable that ESI is inferior to other methods for subject “aw”.

<table>
<thead>
<tr>
<th>Method</th>
<th>Fisher</th>
<th>CSP-rank</th>
<th>ESI</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>aa</td>
<td>79.5238</td>
<td>69.4643</td>
<td>75.2381</td>
<td>74.7421</td>
</tr>
<tr>
<td>al</td>
<td>92.5909</td>
<td>91.1429</td>
<td>94.0714</td>
<td>92.5714</td>
</tr>
<tr>
<td>av</td>
<td>52.4286</td>
<td>64.8214</td>
<td>59.2143</td>
<td>58.8214</td>
</tr>
<tr>
<td>aw</td>
<td>69.9286</td>
<td>76.8452</td>
<td>65.3571</td>
<td>70.6436</td>
</tr>
<tr>
<td>ay</td>
<td>91.9428</td>
<td>91.4864</td>
<td>95.5714</td>
<td>92.3355</td>
</tr>
<tr>
<td>mean</td>
<td>77.2648</td>
<td>78.7320</td>
<td>77.4905</td>
<td>77.8358</td>
</tr>
</tbody>
</table>

Summary

In this paper, we proposed a method based on CWT and ESI algorithm to reduce the channel number and finds those best distinguish between two classes of EEG imagery task. This achieved figure out clearly of electrodes with the help of ESI, which was regarded as the prior channels. The value of the channels was treated as the contribution degree of source location. CSP algorithm and SVM was applied for classification. With the prior channels selected, cut down a large number of channels, the performance of BCI systems keep stable.

However, noise is a factor that can’t be ignored and would greatly influence the selection of channels. Since not all 8-32HZ frequency band includes major information of particular MI, different people with various frequency bands, also diverse source location could produce disparate frequency band. The precise frequency band is beneficial for us to find out the combination of channels. In the future work, we will focus on how to reduce the influence of noise and shrinkage frequency band.

Acknowledgement

This work is financially supported by the National Natural Science Foundation of China (No.81471770) and the Natural Science Foundation of Beijing (No.7132021). We would like Technology for the database. The authors are grateful to the anonymous referee for carefully checking the details and for helpful comments that improved this paper.

References


[21] Information on http://www.leixulab.net/

[22] Information on http://fieldtrip.fcdonders.nl/download.php