EEG Channel Selection Based on Correlation Coefficient for Motor Imagery Classification: A Study on Healthy Subjects and ALS Patient

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Abstract— Brain-Computer Interface (BCI) provides an alternate channel of interaction for people with severe motor disabilities. The Common Spatial Pattern (CSP) algorithm is effective in extracting discriminative features from EEG data for motor imagery-based Brain-Computer Interface (BCI). CSP yields signal from various locations for better performance. In this study, we selected a subset of EEG channels using correlation coefficient of spectral entropy and compared the classification performance using the Filter Bank Common Spatial Pattern (FBCSP) algorithm. We conducted experiments on 4 healthy subjects and one Amyotrophic Lateral Sclerosis (ALS) patient. The results showed that the proposed channel selection method increased classification accuracy of all subjects from 1.25% to 8.22%. Optimal performance was obtained using between 13 to 24 channels, and channels located over the motor cortex zone possess higher probabilities of being selected. Comparing with the channels manually selected to over the motor cortex area, the correlation coefficient method is able to identify the optimal channel combination and improve the motor imagery decoding accuracy of Healthy and ALS subjects.

I. Introduction

Amyotrophic Lateral Sclerosis (ALS) patients, especially at late stage, physically and mentally suffered from being isolated from life activities. Brain-computer interface (BCI) opens a possibility for the patient with server motor disability or neural disorder to communicate and control. Benefiting from the development of computer and neuroscience, BCI system with motor imagery classification becomes a great option for such patients to express themselves through well designed systems. EEG signal, the essential input to BCI system, can be acquired by invasive and non-invasive method. Despite of noise-signal ratio, non-invasive method using scalp EEG acquisition device is commonly used for the reason of cost and safety. International 10-20 system are commonly adopted by researchers for channel placement during an EEG data acquisition process. Effective selection of the channels without compromising the performance of EEG classification is essential for the development of portable EEG applications [1]. Researchers have developed different techniques, including filtering, wrapper, embedded and hybrid techniques [2], for effective selection of EEG channels.

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BCI system with motor imagery yields high classification accuracies for effective information transfer rate in control and communication applications. Filter Bank Common Spatial Pattern (FBCSP) has been recognized as a benchmark for motor imagery classification due to its outstanding performance [3]. However, researchers still facing difficulties to apply motor imagery techniques on general subjects. Research work shows that some subjects experienced hard time in training themselves to use the current BCI systems efficiently [4, 5]. It might due to the challenges from training process, information transfer rate, neural plasticity, nonstationary and noise of signal [6]. Researchers have been actively exploring different techniques to improve the classification performance of general subjects, such as optimal EEG channel selection [2], deep learning with convolution neural networks [7].

In this paper, we investigated the performance of subjects with different options of channel groups for multi-class motor imagery classification. Correlation coefficient of spectral entropy of motor imagery was applied for selection of series channel groups. The performance of the channel groups were evaluated by the FBCSP algorithm. The remaining part of the work is arranged as follow: Section II explains the classification process of motor imagery using FBCSP, and the correlation coefficient method for selection of channel groups. Section III explains the motor imagery experiments on EEG data acquisition from healthy subjects and ALS patient. Section IV discusses the effects of channel group measured by the classification accuracy, and the probability of a channel being selected. The work is concluded in Section V.

II. Methods

Common Spatial Pattern (CSP) diagonalizes the covariance matrix of two data set through Eigen decomposition [7]. The correlation of two data set measures how close they are having a linear relationship. The correlation coefficient is applied in this work to identify the channels which would yield optimal performance for CSP algorithm to construct spatial filter. FBCSP algorithm [9] is chosen to evaluate the performance of the channel groups. In this section, the methods for classification and channel selection are explained in details.

A. Filter Bank Common Spatial Pattern

EEG signal in frequency domain are commonly divided in several bands, i.e delta, theta, alpha, beta and gamma bands [10]. The FBCSP algorithm constructs spatial filters from different frequency bands. Its work flow for multi-class problem is described by the following steps [9]:

1. EEG data E are passed through 9 band filters (4-8Hz, 8-12Hz …36-40Hz);

2. CSP project matrixes W are constructed for each band filtered data. m pairs of CSP features v , as shown in eq (1), are extracted from EEG signal using the first m and last m columns of the CSP projection matrix W,

$$v = log\frac{diag(\overline{W}^T EE^T \overline{W})}{trace(\overline{W}^T EE^T \overline{W})}, \tag{1}$$

where $\overline{W}$ is the first m and last m columns of the projection matrix W ;

3. Naïve Bayesian Parzen Window (NBPW) classifier ω_i, is build using features selected based on the mutual information of each feature (i is the index of the interested class).

4. Classification of EEG trial x is performed based on the posterior probability $P(\omega|x)$ produced by the NBPW classifier with:

$$\omega = arg\, max\, P(\omega_i|x)_{i=1,2\ldots}\ , \tag{2}$$

CSP algorithm only works with two classes of EEG signal. FBCSP algorithm classifies multi-class motor imageries based on an 'interested class versus the rest' strategy. In building NBPW classifier ω_i , all motor imagery data are split into two groups, s_1 and s_2. s_1 contains the motor imagery data for the i^{th} class, such as the right hand motor imagery; and s_2 contains the rest on the motor imageries, i.e the left hand motor imagery and idle motor imagery.

B. Channel Selection

Spectral entropy is a generic measure of disorganization of signal, mathematically expressed as:

$$H(E) = -\sum_{i=1}^{N} p(E_i) log_{10} p(E_i)\ \ , \tag{3}$$

where $E = \{E_1, E_2, \ldots E_N,\}$ is the signal in time domain. $p(E_i)$ is the probability of E_i. It is usually estimated by Burg's algorithm [11]. Spectral entropy separates the background noise from the organized signal, the motor imagery in this study.

The 'interested class versus the rest' strategy is adopted for the channel selection using the correlation coefficient method. EEG data are split into two groups, s_1 and s_2, where s_1 is the group contains class of interest. Spectral entropy H_1 and H_2 is identified corresponding to s_1 and s_2. Correlation of the spectral entropy from the two groups, s_1 and s_2, is an indicator on how close these two groups having a linear relationship, written as:

$$\rho(H_{1,j}, H_{2,j}) = \frac{cov(H_{1,j}, H_{2,j})}{\sigma_{H_1,j}\sigma_{H_2,j}}, \tag{4}$$

where σ_{H_1} is the standard deviation of the respective spectral entropy. j is the index of the channel.

For the purpose of channel selection, we consider the spectral entropy of each channel across all frequency ranges by taking sum of the squared correlation coefficient,

$$P(H_{1,j}, H_{2,j}) = \sum_{i=1}^{N} \rho^2(H_{1,j}, H_{2,j}), \tag{5}$$

where $i = 1 \ldots N$ is the number of frequency bins during estimation of the spectral entropy. Channels are selected based on the ranking of the correlation coefficient among the channels, $P(H_{1,j}, H_{2,j})$. The selected channels C_i is fed to the FBCSP algorithm for feature selection in building of classifier ω_i, where i is the index of the interested class.

III. Experiments

Motor imagery experiments were conducted to acquire data for verification of the channel selection method. All experiments compliant with IRB approved by NUS Institutional Review Board (H-17-009) and SingHealth (CIRS 2016/3092). Four health subjects (S1, S2, S3 and S4, aged at 33.5±2.9, 3 males, 1 female) and one ALS patient in full locked-in stage (P1, aged at 29, female) were recruited for the experiments. *Quik-cap* with 40 electrodes, *Neuroscan* amplifier with *Scan 4.5* were used in scalp EEG data acquisition. All channels refer to the average of A1 and A2 as referencing point. A1 and A2 were placed at left and right ear lobe respectively. Impedance of each channel was maintained below 10 kΩ. Raw EEG data were acquired at 250 Hz filtered by a band pass filter of 0.5 to 40 Hz, and a notch filter of 50 Hz.

In the experiments, subjects were first given 2 seconds of preparation time, then they were instructed to perform one of three motor imagery tasks, i.e. left, right hand and idle motor imagery. Each motor imagery lasted 4 seconds. Left, right hand avatar and a gray disc were displayed on a wide screen monitor to indicate the starting of the left, right and idle motor imagery respectively. After the particular motor imagery task, subjects took a rest of 4 seconds. The health subjects were informed to minimize their eye movement, and the ALS subject was in her complete locked-in stage.

All subjects participated in 2 training experiments in 2 separate days. The healthy subjects performed 3 training sessions in each experiments. Each session includes 10 trials per class. The ALS patient performed 6 and 8 training sessions on experiment 1 and experiment 2. Each session includes 4 trials per class. 30 channels of EEG data, as shown in Figure 1, were used in our subsequent analysis.

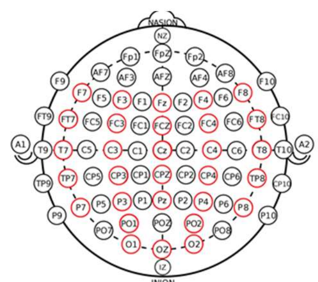

Figure 1 Channel placement (highlighted in red) for motor imagery experiment.

IV. Results and discussion

The effectiveness of the selected group of channels C_i were evaluated by the FBCSP algorithm. Cross validation among experimental sessions on the same day were performed. A sliding window with 2 s width and 0.1 s step in the motor imagery period was applied to form the training and testing data set for classification.

Figure 2 shows the average classification accuracies of each subject, with different channel combinations from group population of 3 to 30 channels. The performance of the FBCSP algorithm increases as the number of channels increases. Its performance reaches the optimal values when the channels are in the range of 13 to 24. The exact number of channels and placement varies from subject to subject. Among the 5 subjects, subject S2 and P1's classification performance were only 5 - 13% above chance level in the 3-class experimental tasks when using data from all 30 channels. This made these group of subjects discouraged in using BCI system. Table 1 shows that the performance of the FBCSP algorithm has been improved on all subjects by using the correlations coefficient channel selection method. Subject S1 and P1's classification accuracies were improved by 8.22% and 5.88%, respectively. S4 was able to achieve classification accuracy of 81.81±2.10% with data from all channels. With the optimized selection of channels, the classification accuracy can be further improved to 83.06±1.58%.

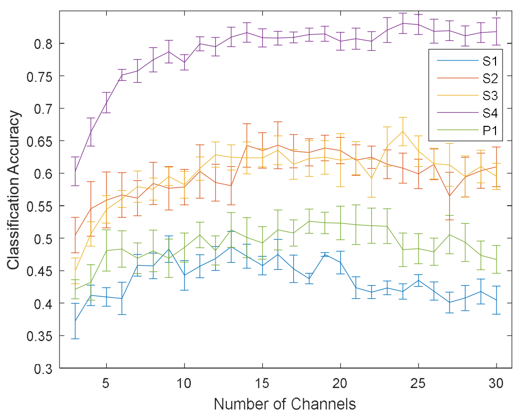

Figure 2 Relationship of average classification accuracies and the number of selected channels from 3 to 30. Vertical bars are the standard errors.

Table 1 Comparison of mean classification accuracies and standard error between 30 channels and the group of channels selected by ranking of correlation coefficient method.

Subject	Mean Classification Accuracies		
	30 channels	Highest from group options	No. of channels
S1	40.44±2.17%	48.66±2.37%	13
S2	60.99±3.04%	64.32±3.63%	16
S3	59.51±2.02%	66.42±2.17%	24
S4	81.81±2.10%	83.06±1.58%	24
P1	46.73±2.14%	52.61±1.87%	18

Figure 2 shows the performance of the FBCSP with the group of channels consisting of between 3 to 30 channels. The probability that a channel was selected is calculated as:

$$p(e_j) = \sum_{n=3}^{30} \epsilon_j / 30 , \quad (6)$$

where e_j is the channel, $j = 1 \dots 30$. $\epsilon_j = 1$ if e_j is selected in the channel group C_j. $n = 3 \dots 30$ corresponds to the groups of selected channels.

Figure 3 shows the probability of each channel been selected on a topological plot. The channels over the motor cortex zone showed higher probabilities of been selected. It indicates the signal acquired over the motor cortex zone has high signal correlation in terms of spectral entropy than that of the peripheral channels. This observation corresponds with the brain's functional framework in neuroscience [9]. It is an evidence showing that the subject was performing the motor imagery task during the experiments. For subjects S2, 4 and P1, it is noticed from Figure 3 that the channels have similar probability of being selected across two experiments. It is an indicator that the subject consistently using the same cortices in performing the motor imagery task across experiments.

Subject S4 gave the highest motor imagery classification accuracy among all the 4 health subjects. Figure 3 (c) and (d), show that subject S4 consistently followed the experimental instructions, and activated his motor cortices during the experiments. Although P1 was in full locked-in stage, which could not provide explicitly feedback on if she was following the experimental instructions. The topological plot of probabilities of selected channels, Figure 3 (e) and (f), show that her respective cortices have been activated accordingly. Figure 3 (a) and (b) show that the channels cover subject S2's left motor cortex and frontal lobe have higher possibilities of being selected. Subject S2 might good at activating his left motor cortex than his right.

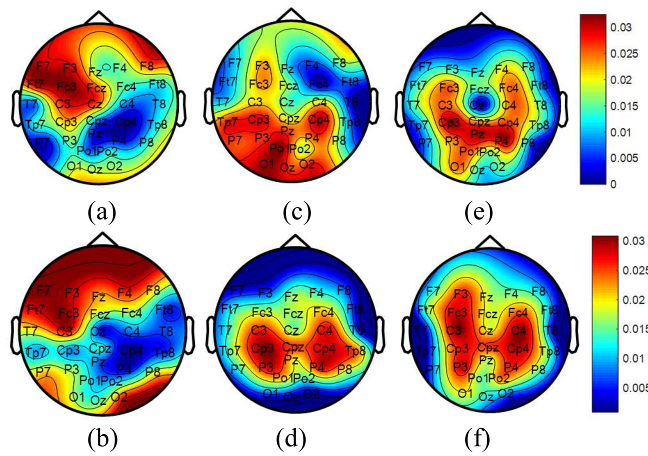

Figure 3 Probabilities of channels been selected based on the ranking of correlation coefficient method. (a) and (b) are from subject S2 for experiment 1 and 2 respectively; (c) and (d) are from subject S4. (e) and (f) are from subject P1.

The functional brain framework shows that motor cortex is responsible for the responsive output [9]. We manually selected five groups of channels to compare the performance of these manually selected channels with that of the channels selected by correlation coefficient method. These manually selected channels spreads from motor cortex to frontal, peripheral and temporal cortices, until the full brain. Table 2 shows the details of these manually selected channels in each group.

Comparison of performances was done over different channel selection methods, i.e. the channels selected by correlation coefficient method, randomly selected, and 5 groups of channels selected manually. Figure 4 shows a comparison on the classification accuracies of Subject S1, 2, 3 and P1 using the above mentioned three methods. The accuracies are higher when using the channels selected by the ranking of correlation coefficient method than that of using the other two methods.

Table 2 manually selected channels

Groups	Manually Selected Channels
1 (3 ch)	C3, Cz, C4
2 (9 ch)	FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4
3 (15 ch)	F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4
4 (21 ch)	F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4, FT7, FT8, Tp7, Tp8, T7, T8
5 (25 ch)	All channels indicated in Figure 1 excluding PO1, PO2, O1, OZ and O2.

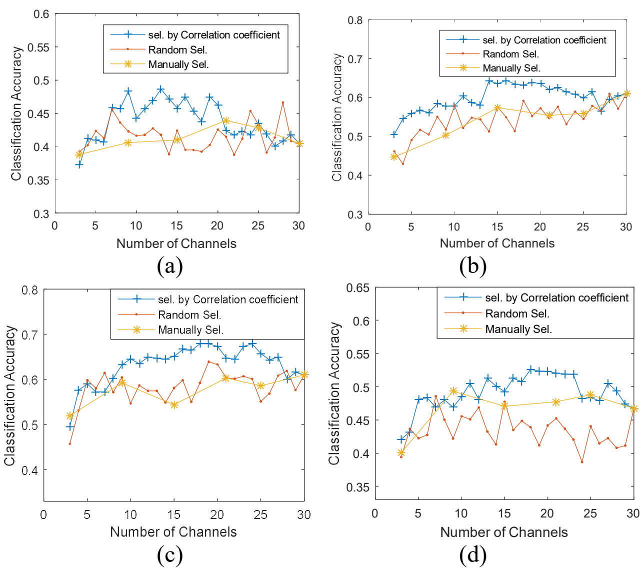

Figure 4 relationship of the average classification accuracies based on correlation coefficient ranking method and random selection of group of channels. (a), (b), (c) and (d) are from subject S1, 2, 3 and P1, respectively.

Channels in the motor cortex area are the domain part in manually selected groups 1, 2 and 3. Comparing the accuracies of these 3 manually selected channel groups with that of the correlation coefficient selected channels, we noticed that the differences in Figure 4 (b), for subject S2, are larger, where such differences in Figure 4 (d), for subject P1, are insignificant. It is because subject S2 is only capable to active left motor cortex during the experiments, as shown in Figure 3 (a) and (b). Hence, the manually selected channel groups which cover mainly the motor cortex area do not work well for his data. The proposed correlation coefficient method looked into channels which have higher correlation coefficient. These channels enabled the classification algorithm had a better performance than using the manually selected channels. Subject P1 demonstrated capabilities in activating both left and right motor cortex, as shown in Figure 3 (e) and (f). The manually selected channels which covered the motor cortex area enabled the classification algorithm to perform. Hence, the differences of performance between the manually selected channels (first 3 groups) and that of the correlation coefficient selected channels are insignificant.

The manually selected channel groups for subject S4 achieved 83.13±2.08%, 82.60±1.94%, 82.11±1.61%, 81.95±1.19% classification accuracy for group option 2, 3, 4 and 5 in Table 2, respectively. The classification accuracies decreased from 83.13% to 81.95% as the number of manually selected channels increased from 9 to 25. It shows the manually selected channels do not necessarily constitute an optimal combination for classification. The channels selected by the correlation coefficient method enabled the classification accuracy to increase from 78.71±1.74% to 83.06±1.58% from 9 to 24 channels. This shows the proposed channel selection method is able to identify the active EEG channel and form an optimal combination for better classification performance.

V. Conclusion

Comparing the classification performance, it is noticed that using full channels of EEG data does not necessarily yield optimal performance. The channel selection method based on ranking of the correlation coefficient is able to identify the optimal channel combination, and improves the classification performance by 1.25% to 8.22% in our experiments. It enhances the performance of both healthy and ALS subjects in using the BCI system. Analysis shows that in some subjects, the placement of the selected channels corresponds to the area where one or both motor cortices are located. These subjects may able to perform motor imagery tasks by activating their motor cortices consistently across experiments. More experiments are required to validate this hypothesis.

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