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A Novel Classification Method for Motor Imagery Based on Brain-Computer Interface

Chih-Yu Chen[1], Chun-Wei Wu[1], Chin-Teng Lin[1,2], *Fellow*, *IEEE,* and Shi-An Chen[1,*]
[1]Brain Research Center, National Chiao Tung University, Hsinchu 300, Taiwan
[2]Depart. of Electrical and Computer Engineering, National Chiao Tung University, Hsinchu 300, Taiwan
*Email: cuteless.ece93g@nctu.edu.tw

Abstract—**Brain computer interface (BCI) is known as a good way to communicate between brain and computer or other device. There are many kinds of physiological signal can operate BCI systems. Motor imagery (MI) has been demonstrated to be a good way to operate a BCI system. In some recent studies about MI based BCI systems, low accuracy rate and time consuming are common problems. In this thesis, a novel motor imagery algorithm is proposed to improve the accuracy rate and computational efficiency at the same time. The architecture of many BCI system is quite complex and they involve time consuming processing. The electroencephalography (EEG) signal is the most commonly used inputs for BCI applications but EEG is often contaminated with noise. To overcome such drawbacks, in this paper we use the common spatial pattern (CSP) for feature extraction from EEG and the linear discriminant analysis (LDA) for motor imagery classification. In this study, CSP and LDA have been used to reduce the artifact and classify MI-based EEG signal. We have used two-level cross validation scheme to determine the subject specific best time window and number of CSP features. We have compared the performance of our system with BCI competition results. This novel algorithm with high accuracy rate and efficiency can be applied to real time BCI system in real-life applications.**

Keywords—Brain-Computer Interface (BCI); Motor imagery (MI); electroencephalography (EEG); common spatial pattern (CSP); linear discriminant analysis (LDA);

I. INTRODUCTION

There are lots of neurons active in our brain continuously day by day; neuron activity can cause electrical waves which we called electroencephalography (EEG). EEG is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In other words, EEG has something to do with the conscious and thought in our brain.

A brain-computer interface (BCI) system tries to understand one's intention primarily based on electroencephalography (EEG) signal and it provides human being a new way to communicate or control [1] . Research on BCI system has become more popular in recent years [2] . Motor imagery (MI) means mental simulation of movement and it has been demonstrated to be a good way to operate a BCI system [3] . Mental imagery of movement can produce EEG patterns over primary sensorimotor area, which is often very similar to execution of actual movement. The state-of-the art literature reveals that it is possible to distinguish between imagined right hand and left hand movements based on single-trial EEG signals [4] .

In recent studies on MI, there are many ways to classify different kinds of MI such as auto regression (AR) [5]. There are many ways to extract useful features for MI recognition [6]; for example, Fast Furrier Transform (FFT) and Common spatial pattern (CSP) [7]. There are some methods which observe the difference in power between the bilateral sides of hemisphere during the imagery, which is a well-known phenomenon of MI. Some of these methods have good result but are too complex [8] or demand too much computing time [9], which is hard to apply in real-time applications. In [7] authors use wavelet packet-based independent component analysis for feature extraction from MI EEG for recognition of complex movements. For BCI application, we need to recognize the fact that different subjects may have different mental conditions and hence, a general classification model is not suitable for all subjects. As a result, we need to develop subject specific classification systems to achieve that to find out a desirable system for the task at hand and that is what we use here. In this thesis, CSP has been used to extract useful features for classification of MI EEG data.

In this study, CSP has been used to extract useful features for classification of MI EEG data and the Linear discriminant analysis (LDA) [10] has been used to classify EEG data. In addition, machine learning [11] method has also been used to improve the feature extraction process. The maximum classification accuracy obtained is 80%. In addition, we have also done an independent component analysis (ICA) [12] to check whether there are distinct sources for the left motor imagery and right motor actions. Our answer is affirmative indicating that the results obtained are quite reliable as well. Because of its high classification rate and simplified computation, we think that the proposed system has the potential to be used in real-time MI-based BCI system [13].

II. METHODS

The experiment data from our laboratory is all recorded in a shielded room. When recording, the subject sits on a comfortable chair, placing his/her hands on a table. The recording system is Neuroscan EEG recording system with 32channels traditional EEG cap as shown in Fig. 1. The

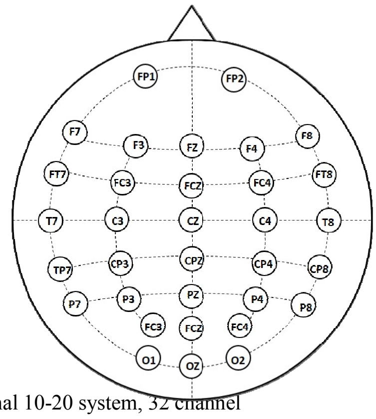

Fig. 1: International 10-20 system, 32 channel

position of electrodes on EEG cap is same as the international 10-20 system shown in Fig. 1.

A. Feature Extraction

We use the Common Spatial Pattern (CSP) [14] for feature extraction. CSP has been successfully used in [15]. We denote the EEG data of trial i for class a byV_a^i, which is a matrix of size N by T. Here N represents the number of channels and T represents the number of sample points in time domain. In the present case we have two classes corresponding to Left-Motor Imagery and Right-Motor Imagery. The corresponding normalized (spatial) covariance matrix, R_a , is calculated as:

$$R_a = \frac{\sum_{i=1}^{na} V_a^i V_a^{iT}}{\sum_{i=1}^{na} trace(V_a^i V_a^{iT})}. \qquad (1)$$

In (1) n_a is the number of trials in class a. Similarly we can compute the normalized (spatial) covariance matrix, R_b for the class b.

Now we can compute the composite covariance matrix R_c as:

$$R_c = R_a + R_b. \qquad (2)$$

And we do the eigen decomposition of R_c,

$$R_c = B_c \lambda B_c^T. \qquad (3)$$

The matrix B_c contains normalized eigenvectors of R_c and λ is a diagonal matrix with eigenvalues of R_c ; both B_c and λ are N by N matrices. Now we use the whitening transformation which scales the principal components

$$W = \lambda^{-1/2} B_c^T. \qquad (4)$$

Then the covariance matrices R_a and R_b are transformed as

$$S_a = W R_a W^T \text{ and } S_b = W R_b W^T. \qquad (5)$$

With this transformation, S_a and S_b share the same common eigenvectors. To find the common eigenvectors of S_a and S_b, the eigen decomposition of S_a is

$$S_a = U \psi_a U^T. \qquad (6)$$

And with the eigenvectors in U

$$S_b = U \psi_b U^T. \qquad (7)$$

Note that $\psi_b + \psi_b = I$, i.e., sum of the two corresponding eigen values is equal to 1.

When the original EEG data are project on U, it maximizes

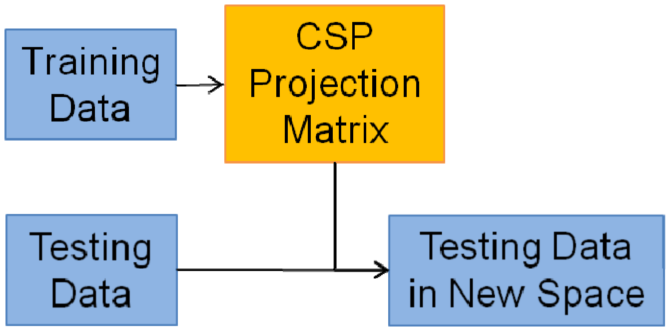

Fig. 2: Relationship of training and testing data in CSP method.

the separation between the two classes as represented by the EEG data. So the projection matrix P is defined as:

$$P = (U^T W)^T. \qquad (8)$$

As shown in

Fig. 2, the projection matrix P is used to project data from each trial into a new space with equation as

$$Z^i = P V^i. \qquad (9)$$

After CSP projection, the first and last m rows are the most discriminative features between class a and b. So we select total 2m rows to represent each trial. Usually, the CSP projections are not used directly as features. Let var_p^i be defined as the variance of row p of Z^i . Then usually the p-th component of the feature vector for the i-th trial is computed as the logarithm of the normalize variance as in (10):

$$f_p^i = \log\left(\frac{var_p^i}{\sum_{p=1}^{2m} var_p^i}\right);\ p=1, \ldots, 2m. \qquad (10)$$

This feature vector $F_i = (f_1^i, \ldots, f_{2p}^i)^T$ is then used for designing classifier for motor imaginary actions.

To see the difference between the original EEG data and

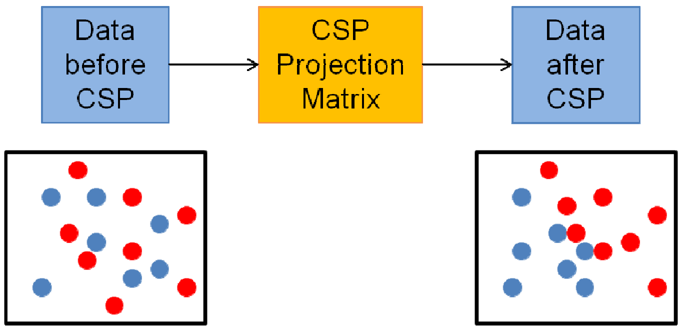

Fig. 3: Comparison of data scatter map before and after CSP projection

the data after CSP projection, the data are plotted in 2 dimensions as shown in Fig. 3. Principal component analysis (PCA) is use to sort the importance of each dimension before CSP projection. The first and second dimension is used to plot

2D scatter map. In the other hand, because the first and last row after CSP projection contains the most discriminative information [16], so the feature of the first and last row are used to plot this 2D scatter map.

B. Classifier Design

Linear Discriminate analysis (LDA) [18] is a well-known classification method which projects data in a new space using a projection, $y = w^T x$, which minimizes the within class

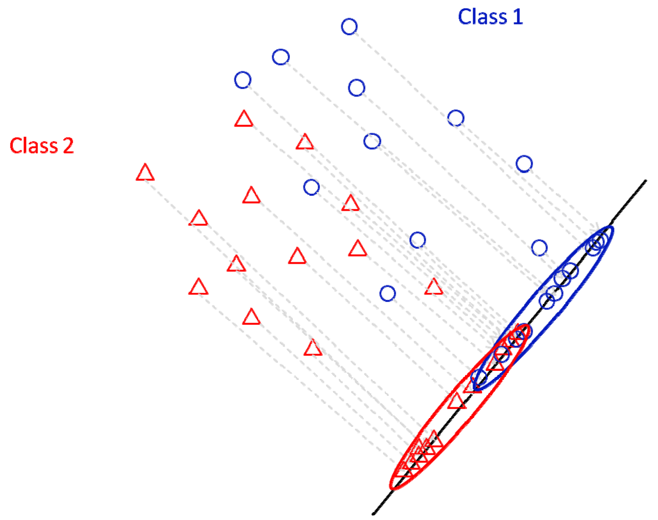

Fig. 4: Linear Discriminate analysis (LDA) projection

scatter and maximizes the scatter between classes as shown in Fig. 4.

III. Results and Discussions

A. Our Experiment Procedure

The procedure followed in our experiment is shown in Fig 5. A subject sits on a comfortable chair, placing his/her hands on a table. In the beginning of each trial, the screen is kept blank for 2 seconds. After that, a cross is displayed on the center of the screen for 2 seconds, and then an arrow point either to left or to right would randomly appear on the screen

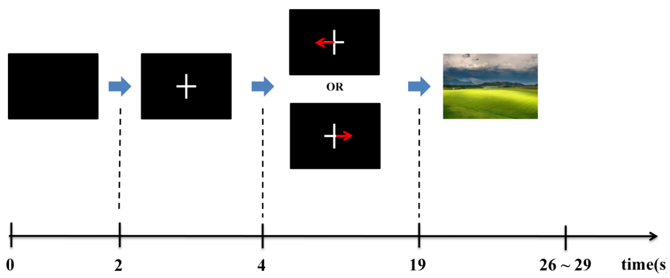

Fig. 5. The design of our experiment: the screen is kept blank for 2 seconds and then a cross is shown at the center of screen for 2 seconds, after that a left or right arrow shows up randomly to cue the subject to do left/right motor imagery for 15 seconds, then a picture is show on the screen for a period between 7sec and 10 seconds, the exact duration is decided randomly.

for 15 seconds. When the subject sees the arrow pointing to left, he is asked to do the imagery of left hand movement and vice versa. After the imagery, a picture would be displayed on

Table 1: Comparison between different kinds of classification method on our experiment data.

Classification Result of Experiment Data Recorded in Our Laboratory 100 x 10-fold cross-validation				
	BCILAB	Multi-band	Voting scheme	Probability Summation
Subject 1	95.6 ± 5.2 %	96.7 ± 4.1 %	94.4 ± 5.6 %	**97.5 ± 3.9 %**
Subject 2	96.9 ± 6.5 %	96.5 ± 5.2 %	93.9 ± 6.4 %	**97.2 ± 4.1 %**
Subject 3	73.8 ± 14.2 %	75.2 ±11.0 %	71.8 ± 11.2 %	**88.0 ± 8.7 %**
Subject 4	80.6 ± 11.6 %	90.6 ± 6.9 %	90.8 ± 6.9 %	**92.8 ± 6.2 %**
Subject 5	65.9 ± 9.7 %	95.8 ± 11.4 %	89.5 ± 7.7 %	**97.7 ± 3.7 %**

the screen for a period between 7 to 10 seconds, randomly decided, to help subjects relax between trials.

B. Classification Performance

The result of these different classification methods is shown in Table 1.

From both result of BCI competition data and experiment data recorded in our laboratory, probability summation has higher mean accuracy rate and smaller variance which prove the probability method is effective and stable. Compare the multiple band method and voting scheme, voting scheme is only better on result of subject A and subject 4. This might because of the situation mentioned above that some band hard to classify still become one vote. The probability summation method even makes great improvement on subject F, subject 3 and subject 5. As a result, the probability summation method

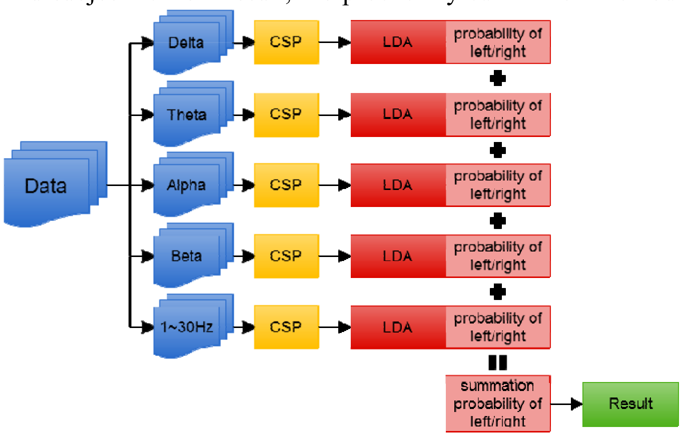

Fig. 6: The structure of novel motor imagery algorithm

is selected as the algorithm of our BCI system. After the comparison, the structure of motor imagery algorithm is selected as shown in Fig. . This structure is selected because it can extract more features by multiple frequency band, can avoid misclassification caused by voting scheme and has high accuracy rate.

A further test is applied here to recheck the model reliability. This test is to evaluate the performance of algorithm on data from the same subject but from another day. This test is to confirm the model is reliable. The training set including 4 sessions of experiment (160 trials), recorded continuously in one day from a subject. Then, the testing set including 2 sessions of experiment (80 trials), recorded on another day from the same subject. After the model generated by training set, the model apply to testing data to evaluate the performance. The accuracy rate of prediction is 91.250% which means the model is stable.

IV. Conclusions

In this study, we have used common spatial patterns for feature extraction and linear discriminant analysis for motor imagery classification based on EEG signals. The developed method uses CSP and LDA with data from 32 channels. A novel classification method is proposed to solve the misclassifying problem caused by voting scheme — High classification accuracy rate on the three datasets and well-performed computational efficiency can be obtained. This motor imagery based BCI system is high efficient, real-time and can be utilized in our daily life.

The motor imagery algorithm on brain-computer interface yield good classification rate—which can be used to real-life applications (e.g. robot and wheel chair) with online user interface. However, the motor imagery based BCI system currently still need computer to further build classification model and process online data through the proposed motor imagery algorithm. Consequently, in the following research stage, we're going to develop the novel algorithm on embedded system, which is integrated in the brain-computer interface system. Through the innovative algorithm-device integration, the motor imagery based BCI system will become a computer-free, convenient and more practicable system.

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