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EEG Based Brain Computer Interface Hand Grasp Control: Feature Extraction Method MTCSP

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Abstract

Brain-Computer Interfaces (BCIs) are communication systems, which enable users to send commands to computers by using brain activity only; this activity being generally measured by Electroencephalography (EEG). BCIs are generally designed according to a pattern recognition approach, i.e., by extracting features from EEG signals, and by using a classifier to identify the user's mental state from such features. In this study, we have considered the BCI Competition data sets 2b-2008; additionally, Multi-Taper Common Spatial Pattern (MTCSP) feature extraction method is used for extracting the features of right and left hand data, Logistic Regression (Logreg) classifier is chosen to classify the data sets. In this paper, TPR, FPR, ACC and k function are used as evaluation criteria. The comparison of the results with the results of the BCI competition 2008 has proved the effectiveness, high accuracy and resolution of the proposed method. The results have shown that MTCSP method provides even higher classification accuracy. It points out that utilizing suitable preprocessing to keep the EEG signal free of redundant information is for sure a very important in the BCI development.

Keywords: Brain-Computer Interfaces (BCI), Feature extraction, Multi-Taper Common Spatial Pattern (MTCSP)

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1. Introduction

For several years, many efforts have been done to use the electro-encephalogram (EEG) as a new communication channel between human brain and computer. This new communication channel is called EEG-based brain-computer interface (BCI). Most of these efforts have been dedicated to the improvement of the accuracy and capacity of this EEG-based communication channel. Several factors may affect the performance of the BCI. These factors include the brain signal used as the input of the BCI, the signal processing methods used for feature selection and classification, cognitive tasks to be intended, and subject training. Different types of brain signals are used to detect the subjects' intention. Thus far, slow cortical potentials (Hinterberger et al., 2004), oscillatory EEG activity (Mason and Brich, 2000; Pfurtscheller and Neuper, 2001; Wolpaw et al., 2000) and various types of event-related potentials including readiness potential (Barke et al., 2005), steady-state visual-evoked potential (SSVEP) (Pfurtscheller et al., 1998) and P300 (Serby et al., 2005) have been utilized in different BCI systems (Erfanian and Erfani, 2004).

To classify the EEG patterns, feature vectors must be created. The classification performance is profoundly affected by the choice of feature set. Even when the features presented contain enough information about the output class, they may not predict the output correctly because the dimension of feature space may be so large that it may require numerous instances to determine the relationship. It was reported that the performance of classifier systems deteriorates as new irrelevant features are added (Erfanian and Erfani, 2004; Kwak, 2003). The process of BCIs systems have been shown in Fig. 1.

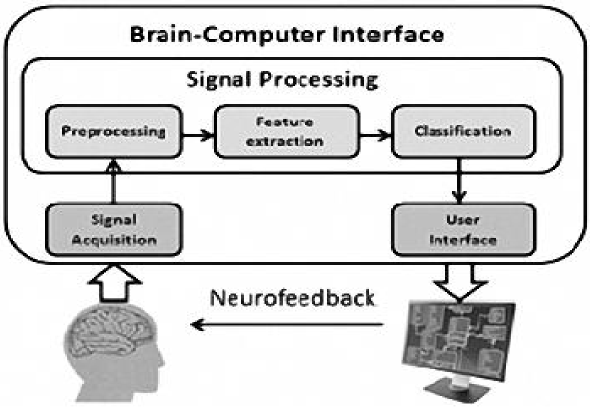

Fig. 1. BCI block diagram (Kolodziei et al., 2012).

EEG-based BCIs systems measure specific features of EEG activity and translate these features into device commands. One of the most difficult problems in BCI development is the restricted data throughput that can be achieved (Wolpaw, 2002). This information transfer rate needs to be improved, and often a balance must be maintained between accuracy and speed one way for improving this problem is to consider the use of multiple classes. Furthermore, there is always a search for a method which can lead to a better result and higher accuracy (Manoochehri, 2010). BCI is composed of signal collection and processing, pattern identification and control systems (Liu et al., 2005; Suleiman et al., 2010). The purpose of this study is to control the hand grasp for both right and left hand. We have used BCI Competition data sets 2b-2008 and Multi-Taper Common Spatial Pattern (MTCSP) feature extraction method has been used for extracting the features of right and left hand data. Logistic Regression classifier (Logreg) has been chosen to classify the data. Results of this methods have been compared with the results of the BCI Competition 2008 data sets 2b. The MTCSP method was originally proposed (Muller-Gerking et al., 1999; Ramoser et al., 2000). This method leads to a projection matrix, the rows of which function as discriminative spatial filters only distinguishing between two conditions.

Having signals projected with projection matrix computed from training trials, the features for classification proper are vectors whose elements are the variances of the projected signals (Manoochehri et al., 2010). The MTCSP algorithm is often used to optimally discriminate between two classes of EEG data based on simultaneous diagonalization of two covariance matrices (Ramoser et al., 2000). Logistic Regression is an approach to learning functions of the form f*:* $X \rightarrow Y$, or P(*Y*/*X*) in the case where *Y* is discrete-valued, and X= $<X_1.....X_n>$ is any vector containing discrete or continuous variables (Mitchell, 2015) (Fig. 2).

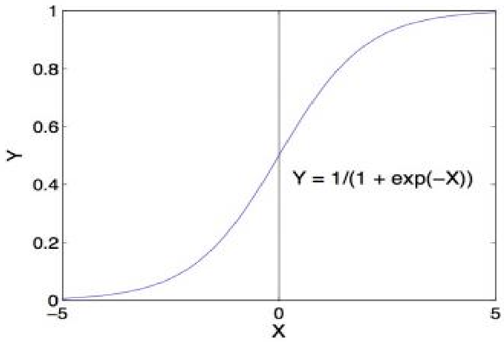

Fig. 2. Form of the logistic function. In Logistic Regression, P(*Y*/*X*) is assumed to follow this form (Mitchell, 2015).

2. Methods

In this paper, at first, data sets were collected, subsequently, eye artifacts were removed by Adaptive Noise Canceller (ANC). Multi-Taper Common Spatial Pattern (MTCSP) is used for feature extraction. Finally, Logreg classifier is used for classification and evaluation (Fig. 3).

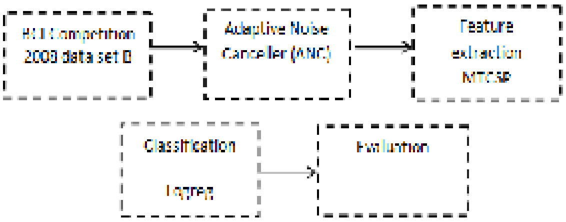

Fig. 3. BCI block diagram.

2.1. Datasets

In this work, BCI Competition 2008 -Graz data set B is used. This data set consists of EEG data from 9 subjects who were right-handed and had normal or corrected-to-normal vision they also were paid for participating in the experiments. All volunteers were sitting in an armchair, watching a screen monitor placed approximately 1m away at eye level. Depending on the cue visual stimuli which appears on the monitor of the computer, subject imagines the hand grasping or opening for right and left hand. If the visual stimuli does not appear, the subject does not perform a specific task. For each subject, 5 sessions are provided, whereby the first two sessions contain training data without feedback (screening), and the last three sessions were recorded with feedback. In this study, we used the cue-based screening paradigm consisting of two classes, namely the motor imagery (MI) of left hand (class 1) and right hand (class 2) which is comprised of 9 trials for right hand and 9 trials for left hand for each person. Three bipolar recordings (C3, Cz and C4) were recorded with a sampling frequency of 250 Hz. They were band pass filtered between 0.5 Hz and 100 Hz, and a notch filter at 50 Hz was enabled. At the beginning of each session, a recording of approximately 5 minutes was performed to estimate the EOG influence. The recording was divided into three blocks: (1) Two minutes with eyes open, (2) One minute with eyes closed, and (3) One minute with eye movements (Leeb et al., 2008). ANC filters using neural network has been utilized for real-time removing the eye blinks interference from the EEG signals (Singh, 2001).

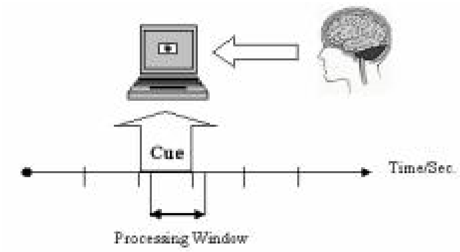

Fig. 3. Imagination of hand movement.

2.2. Multi-Taper Common Spatial Pattern (MTCSP)

In this study we used BCILAB for applying MTCSP algorithm and Logreg classification. MTCSP is a experimental paradigm for all-frequency Common Spatial Patterns. The basic idea is to calculate CSP for each covariance matrix in the cross-spectrum, and to use multi-taper spectral estimation to ensure an optimal tradeoff between spectral precision and estimation noise. The default classifier is sparse logistic regression with elastic-net penalty. This paradigm also implements a second approach in which the cross-spectrum is not spatially filtered, but directly submitted to the classifier (Disciplined Cross-Spectral Regression). Table 1 indicates the parameters of BCILAB.

Table 1
Parameters of BCILAB.

data = io_loadset('data sets/mary/nback.eeg')	
My approach	MTCSP
Sampling rate after resampling	250
Epoch window relative to the target markers	[0.5 3.5]
Type of window function	Rect
Frequency range of interest	[1 45]
Spectral smoothing	5
Sub-sample the spectrum	1
Target markers	{'769 ','768'}
CSP pattern per band (times two)	3
Machine learning function	Logreg

2.3. Evaluation criteria sample to sample

We use this method to evaluate the performance of the classifier to estimate the classifier accuracy. This method is suitable for dividing different imagination each one another. In this work we use it for dividing imagination of right hand and left hand movement. There are two criteria TPR and FPR.

$$FPR = \frac{FP}{FP + TP}$$
$$TPR = \frac{TP}{TP + FN} \qquad (1)$$

Where, TP is the number of true positive, FP is the number of false positive, TN is the number of true negative, FN is the number of false negative. TPR shows the rate of the true detection and FPR says the rate of false detection. Whatever the rate of TPR is so much more and FPR is so much less classification is better. In good condition TPR is 1 and FPR is 0 (Blinowska and Zygierwicz, 2012).

2.3.1. Classification Accuracy and Error Rate (ACC and ERR)

The Classification Accuracy (ACC) or the error rate are the most widely used evaluation criteria in BCI research. Nine out of fourteen datasets in the BCI competitions 2003 and 2005 used the accuracy or the error rate as the evaluation criterion. One possible reason for its popularity is that it can be very easily calculated and interpreted. However, it is important to note that the accuracy of a trivial (random) classifier is already 100%/M, (e.g. for M = 2 classes 50% are correct just by chance). If the ACC is smaller than this limit, an error occurred and further exploration is required. On the other hand, the maximum accuracy can never exceed 100%. Sometimes, this could be a disadvantage, especially when two classification systems should be compared and both provide a result close to 100% (Guyton, 1956).

$$ERR = 1 - ACC \qquad (2)$$

$$ACC = P_0 = \frac{\sum_{i=1}^{M} n_{ii}}{N} \qquad (3)$$

$$N = \sum_{i=1}^{M} \sum_{j=1}^{M} n_{ij} \qquad (4)$$

Where N, is the number of the total samples and n_{ii} is the total number of samples which were detected correctly (Guyton, 1956).

2.3.2. Cohen's Kappa Coefficient (k)

Cohen's kappa coefficient k addresses several of the critiques on the accuracy measure. The calculation of k uses the overall agreement P_0 = ACC, which is equal to the classification accuracy, and the chance agreement P_e.

$$k = \frac{P_0 - P_e}{1 - P_e} \qquad (5)$$

$$P_e = \frac{\sum_{i=1}^{M} n_{:i}\, n_{:i}}{N^2} \qquad (6)$$

With $n_{:i}$ and $n_{i:}$ being the sum of the ith column and the ith row, respectively. The kappa coefficient is zero if the predicted classes show no correlation with the actual classes. A kappa coefficient of 1 indicates perfect classification. Kappa values smaller than zero indicate that the classifier suggests a different assignment between output and the true classes (Guyton, 1956).

3. Results

Tables 1 and 2 show the results of the classification of suggested method in BCILAB and evaluating k for left hand data sets. Tables 3 and 4 show the results of the classification and evaluating k for right hand data sets .

Table 1
Results of the left hand data sets classification.

Sub	TPR	FPR	ERR	ACC
1	0.992	0.050	0.022	0.978
2	0.975	0.217	0.089	0.911
3	0.908	0.083	0.089	0.911
4	0.975	0.100	0.050	0.950
5	0.975	0.033	0.028	0.972
6	0.975	0.017	0.022	0.978
7	1	0.083	0.028	0.972
8	0.938	0.212	0.113	0.887
9	0.992	0.083	0.033	0.967

Table 2
Results of evaluating k for left hand data sets.

Sub	$P_0 = ACC$	$k = \frac{P_0 - P_e}{1 - P_e}$ $P_e = \frac{1}{M = 2}$
1	0.978	0.96
2	0.911	0.82
3	0.911	0.82
4	0.95	0.90
5	0.972	0.94
6	0.978	0.96
7	0.972	0.94
8	0.887	0.77
9	0.967	0.93

Table 3
Results of the right hand data sets classification.

Sub	TPR	FPR	ERR	ACC
1	0.992	0.067	0.028	0.972
2	0.967	0.250	0.106	0.894
3	0.908	0.150	0.111	0.889
4	1	0.014	0.005	0.995
5	1	0	0	1
6	0.967	0.067	0.044	0.956
7	1	0	0	1
8	0.967	0.100	0.056	0.944
9	0.975	0.167	0.072	0.928

Table 4
Results of evaluating k for right hand data sets.

Sub	$P_0 = ACC$	$k = \frac{P_0 - P_e}{1 - P_e}$ $P_e = \frac{1}{M = 2}$
1	0.972	0.94
2	0.894	0.79
3	0.889	0.78
4	0.995	0.99
5	1	1
6	0.956	0.91
7	1	1
8	0.944	0.89
9	0.928	0.86

4. Conclusion

In this work, we present and analysis the ability and performance of MTCSP as a feature extraction method and Logreg classifier for left and right hand opening and grasping control. Results for left hand data sets show that TPR is in the ranges of 0.908 ~ 1, FPR is in the ranges of 0.017 ~ 0.217, ACC is in the ranges of 0.887 ~ 0.978, K is in the ranges of 0.77 ~ 0.96. Results for right hand data sets show that TPR is in the ranges of 0.908 ~ 1, FPR is in the ranges of 0 ~ 0.250, ACC is in the ranges of 0.889 ~ 1, K is in the ranges of 0.78 ~ 1. So TPR is higher than FPR, ACC is well and it approaches to 1, k > 0 and almost 1.

In Tables 5 and 6 results of the classification of left and right hand date sets have been comprised of the results of BCI competition 2008 data sets 2b and K average is considered for them. According to the tables of K average, the suggested method is desirable and improvement of results is shown. Therefore, the MTCSP algorithm is a feature extraction method that can learn spatial filters maximizing the discriminability of two classes. MTCSP has been proven to be one of the most popular and efficient algorithms for BCI design, notably during BCI competitions. Despite its popularity and efficiency, MTCSP is also known to be highly sensitive to noise and to severely over fit with small training sets. Since EEG measurements are generally contaminated by artifacts and noise, the MTCSP algorithm is, thus, highly sensitive to these contaminants. This motivated the research for sparse solutions in the MTCSP algorithm. In these methods, the sparse spatial filters project the signals in the most discriminative direction based on a smaller number of electrodes at the expense of lowering the accuracy. These patterns maximize the difference between the populations and have been proved to be a powerful and successful method for the accurate detection and recognition of brain patterns.

Table 5

Comparison the results of the left hand data with results of the BCI competition 2008 data set2b.

Scientists	Preprocessing	Feature Extraction	Classifiers	Calculation of K for subjects 1	2	3	4	5	6	7	8	9	K Average
Suggested method	EOG removal with ANC	CSP	LDA	0.96	0.82	0.82	0.90	0.94	0.96	0.94	0.77	0.93	0.89
Zheng Yang Chin [25]	Artifact removal with bandpass filter	FBCSP	NBPW	0.40	0.21	0.22	0.95	0.86	0.61	0.56	0.85	0.74	0.60
Huang Gan [26]	EOG removal with bandpass filter	CSSD	LDA	0.42	0.21	0.14	0.94	0.71	0.62	0.61	0.84	0.78	0.58
Damien Coyle [27]	NTSPP	One side sliding window	LDA SVM	0.19	0.12	0.12	0.77	0.57	0.49	0.38	0.85	0.61	0.46
Shaun Lodder [28]	N/A	Wavelet	LDA	0.23	0.31	0.07	0.91	0.24	0.42	0.41	0.74	0.53	0.43
Jaime Fernando Delgado Saa [29]	EOG removal with linear regression, highpass filter	Spectral feature in the mu and beta bands	Neural network	0.20	0.16	0.16	0.73	0.21	0.19	0.39	0.86	0.44	0.37
Yang Ping [30]	EOG removal with regression analysis	Band power feature, RFE	LDA	0.02	0.09	0.07	0.43	0.25	0.00	0.14	0.76	0.47	0.25

Table 6

Comparison the results of the left hand data with results of the BCI competition 2008 data set2b

Scientists	Preprocessing	Feature Extraction	Classifiers	Calculation of K for subjects 1	2	3	4	5	6	7	8	9	K Average
Suggested method	EOG removal with ANC	CSP	LDA	0.94	0.79	0.78	0.99	1	0.91	1	0.89	0.86	0.90
Zheng Yang Chin [24]	Artifact removal with bandpass filter	FBCSP	NBPW	0.40	0.21	0.22	0.95	0.86	0.61	0.56	0.85	0.74	0.60
Huang Gan [25]	EOG removal with bandpass filter	CSSD	LDA	0.42	0.21	0.14	0.94	0.71	0.62	0.61	0.84	0.78	0.58
Damien Coyle [26]	NTSPP	One side sliding window	LDA SVM	0.19	0.12	0.12	0.77	0.57	0.49	0.38	0.85	0.61	0.46
Shaun Lodder [27]	N/A	Wavelet	LDA	0.23	0.31	0.07	0.91	0.24	0.42	0.41	0.74	0.53	0.43
Jaime Fernando Delgado Saa [28]	EOG removal with linear regression, highpass filter	Spectral feature in the mu and beta bands	Neural network	0.20	0.16	0.16	0.73	0.21	0.19	0.39	0.86	0.44	0.37
Yang Ping [29]	EOG removal with regression analysis	Band power feature, RFE	LDA	0.02	0.09	0.07	0.43	0.25	0.00	0.14	0.76	0.47	0.25

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