BAGGING REGULARIZED COMMON SPATIAL PATTERN WITH HYBRID MOTOR IMAGERY AND MYOELECTRIC SIGNAL

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ABSTRACT

Common Spatial Pattern(CSP) is a widely used algorithm in BCI application. However, it is sensitive to noise and artifact. In this paper, we propose a bagging regularized common spatial pattern (Bagging RCSP) approach for BCI with hybrid motor imagery and myoelectric signal. We divide the training samples into packets and choose training packets by Bagging to extract RCSP features. Furthermore, LDA is used to project the feature vector to lower space. In the end, a classification algorithm based on NNC is adopted. The Off-line experiment on BCI competition III attests Bagging RCSP versatile. The accuracy increases by 3%-5% in average than RCSP-A results. Furthermore, we designed and realized an online BCI system based on Bagging RCSP and evaluated through experiment involving four experimenters performing the BCI system of catching the apples. The results show the effectiveness of the proposed approach and the real time BCI system.

Index Terms**—**Brain-computer interface(BCI), EEG, motor imagery, Bagging RCSP, real-time system

1. INTRODUCTION

With the development of science technology, Brain-Computer Interfaces(BCI) embodies the dream of manipulating reality by our mind. Generally, BCI system utilizes electrophysiological signals to decode user's intent into control commands, ensuing with driving other device[1]. Owing to its non-invasive and low-cost, most BCI system favors electroencephalogram(EEG) to acquire the signals[2].

Nowadays, BCI research concentrates on motor-imagery, P300[3], SSVEP and so on, which are typical signals that are triggered in certain cases. Among them especially motor-imagery(MI) has attracted much focus by reason that it appears without complex condition. Study on motor imagery indicates that different imagined movements would induce suppression or enhancement on mu(8-12Hz) and beta(18-26Hz) rhythms activity and power spectrum, which is known as event-related desynchronization/ synchronization(ERD/ERS)[4]. However, the low signal-to-noise rate problem critically impedes its commercial application. Traditional Common Spatial Pattern(CSP) was proved to be an effective method to extract information of discriminating different classes in motor imagery. Key of the CSP is the joint diagonalization method, which maximizes the variance of one class while minimizes the other.

Although CSP is popular and efficient, its weakness also highlights. The main drawback is that it is sensitive to noise and artifacts[5]. In this circumstance, subsequently methods based on CSP, for example, CCSP[6], SSCSP[7], RCSP[8], FERCSP[9], FBCSP[10], were proposed. Adding prior information into the CSP learning process is recognized the most impactful, which is well-known as Regularized Common Spatial Pattern(RCSP)[8]. In RCSP method, it introduces other people's data deliberately to ensure the bias-variance of subject, which leads to a higher performance than CSP, especially in the small training set[8]. However, there is no clear point on the relationship between accuracy and the number of other people's EEG data. Importantly, until now there is no practical BCI system based on a small training set.

In this paper, we elaborate an attempt in putting RCSP into application, i.e., Bagging Regularized Common Spatial Pattern(Bagging RCSP). Based on it, we design a real-time system to control the game role's movement. Different from previous 1-D control application that only give binary classification result, we utilize myoelectric signal and motor imagery to control the role's walk state and direction respectively. In the direction control, EEG is firstly bandpass filtered in 0.1-30Hz. Then it automatically selects training data by Bagging to extract RCSP features. Furthermore, LDA is used to project the feature vector to lower space. In the end, a classification algorithm based on NNC is adopted. The real-time system enables people to control direction via this Bagging RCSP algorithm to discriminate left or right hand motor imagery.

Rest of this paper proceeds as follows. The next section shall firstly explain the online system in detail, including the system mechanism, Bagging RCSP and the system control algorithm. Then a series of experiments are conducted in section III. Section IV will analysis and discuss the results. Section V concludes the paper.

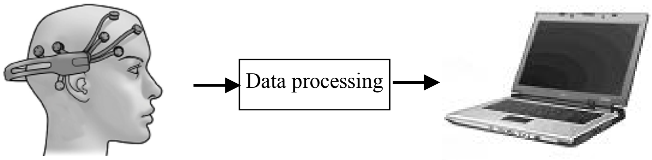
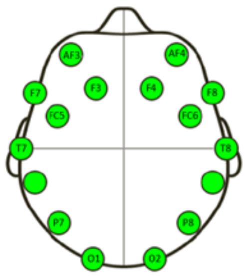


Fig.1. BCI system architecture.



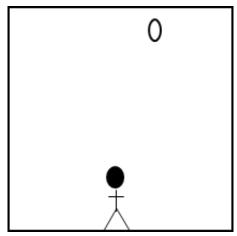


Fig.2. Distribution of electrodes. Fig. 3. GUI of BCI system.

2. SYSTEM DESIGN

2.1. System hardware and environment

This system comprising two main components: an EEG signal sampling device and a computer system shows in Fig. 1. Designing a practical system emphasizes simplicity and wearability. So we choose Emotiv as the sampling device. It has 16 channels, and records the electric potentials at sampling rate of 128Hz. Excluding the horizontal electrooculography channel and vertical electrooculography channel which record the eye movements, remaining 14 channels are used. Distribution of channels is depicted in Fig. 2.

2.2. BCI system rule and mechanism

2.2.1. System rule

This system can be epitomed briefly as “catch the apple”. User controls the role to stop walking by gritting teeth, while to move left or right by corresponding hand motor imagery respectively. GUI is illustrated in Fig. 3, where the stickman represents the role, and the ball denotes a falling apple. Size of the GUI is 700 pixels height × 700 pixels width, and the stickman is 100 pixels height × 100 pixels width.

Game starts when the stickman appears in the center of bottom. After 1s, an apple randomly shows at the top and begin falling slowly. Importantly, the velocity of the apple and stick are designed appropriately to ensure enough time to catch the apple. To be specific, the stickman’s step size is 100 pixels, while the velocity of the apple is 30 pixels per second. Like other online system, control commands depends on the user’s mental activities[11][12].

2.2.2. The Bagging RCSP algorithm

Bagging RCSP inherits the essence of RCSP. It is interesting idea when using RCSP in practical rather than an new algorithm. Based on the low increment of accuracy with growing training number, we divide the training samples into packets. Furthermore, we choose training packets by Bagging to extract RCSP features, respectively.

A single trial EEG signal is recorded by a matrix D of N × T, where N represents the number of channels, T is the sampling number. Then normalized covariance matrix is

$$C = \frac{DD^T}{trace(DD^T)} \tag{1}$$

where D^T means the transpose of D, and trace(d) denotes the sum of diagonal elements of matrix d. Then the average covariance of EEG can be derived from formulation (2). M denotes the number of trials, and i refers to the motor imagery class, including left and right.

$$\overline{C_i} = \frac{1}{M}\sum_{m=1}^{M} C_{\{i,m\}} \tag{2}$$

In order to decrease the variance bias of estimate covariance, RCSP computes the covariance matrix with the specific subject’s EEG as well as others individuals’[8]. The formulation is as follows:

$$S_i(\beta,\gamma) = (1-\gamma)\mathrm{X}_i(\beta) + \frac{\gamma}{N} trace[\mathrm{X}_i(\beta)]\cdot I \tag{3}$$

In the above formulation, $\mathrm{X}_i(\beta)$ refers to:

$$\mathrm{X}_i(\beta) = \frac{(1-\beta)\cdot C_i + \beta\cdot C_i^{'}}{(1-\beta)\cdot M + \beta\cdot M^{'}} \tag{4}$$

where C_i means the covariance matrix of M trials in class i from the specific folk, $C_i^{'}$ means the covariance matrix of $M^{'}$ trials in class i from other people.

Inspired by CSP, the covariance can be composited as follows:

$$S(\beta,\gamma) = S_{\mathrm{left}}(\beta,\gamma) + S_{right}(\beta,\gamma) = \mathrm{EVE}^T \tag{5}$$

where E means the eigenvectors matrix in corresponding to the eigenvalue matrix V. Then whitening matrix is:

$$P = V^{1/2}E^T \tag{6}$$

So

$$P\cdot S(\beta,\gamma)\cdot P^T = \mathrm{c}\cdot \mathrm{I} \tag{7}$$

where c is a constant. Hence, $S_{\mathrm{left}}(\beta,\gamma)$ shares the same eigenvectors with $S_{right}(\beta,\gamma)$

$$\begin{aligned} S_{\mathrm{left}}(\beta,\gamma) &= UV_{left}U^T \\ S_{right}(\beta,\gamma) &= UV_{right}U^T \end{aligned} \tag{8}$$

Then we can conclude the projection matrix $W = U^T P$.

Similar to CSP, RCSP choose the first and last r columns of W to project a single trial D.

$$Z = WD \tag{9}$$

Then the discriminative feature vector y is constructed as follows:

$$y_q = \log\left(\frac{\mathrm{var}(z_q)}{\sum_{q=1}^{2r}\mathrm{var}(z_q)}\right) \tag{10}$$

Table 1. Performance comparison of CSP, RCSP and Bagging RCSP on Competition III data set IVa.

Data Set IVa, BCI Competition III							
Algorithm	**aa**	**al**	**av**	**aw**	**ay**	**average**	**time(s)**
CSP	66.1	98.2	59.2	88.4	61.1	74.6	5.5
LW-CSP	69.6	100.0	56.6	93.3	67.1	77.3	-
SSCSP[7]	73.2	96.4	54.8	70.5	73.4	73.5	-
RCSP-A[15]	76.8	98.2	74.5	92.9	77.0	83.9	62.2
FERCSP[9]	79.5	96.4	77.6	94.2	82.5	86.0	300.3
BRCSP	79.3	98.6	78.3	92.9	82.5	86.3	63.3

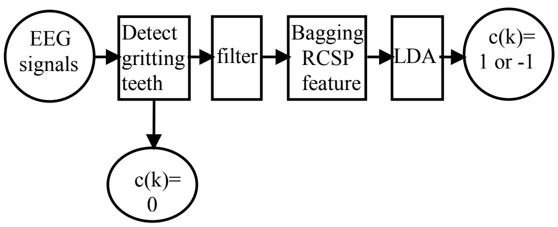


Fig. 4. Diagram of BCI system mechanism.

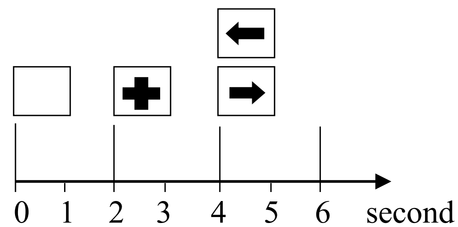


Fig. 5. Paradigm of a calibration trial

2.2.3. System mechanism

The stickman's movement is determined by detection result of motor imagery and myoelectric signals. Its position model is

$$x(k+1) = x(k) + c(k) \cdot v_s \tag{11}$$

where $c(k)$ denotes the k th judgement: -1 for "left", 0 for "stop", 1 for "right". Diagram of the algorithm shows in Fig. 4. Firstly, system acquires EEG by a 2s window ending at the current time point. Then it determines the walking state via myoelectric signals. In details, electrodes potential will exceed a certain threshold if user grits his/her teeth. In this circumstance, system judges the user to "stop", otherwise it jumps to the motor-imagery module: 1) bandpass filtering in 0.1-30Hz.; 2) selecting generic data by bagging and extracting RCSP features; 3) projecting feature to a low-dimensional space by FDA; 4) NNC classifier. Then system will refresh the canvas to show the stickman in the new position.

Threshold in detection of gritting teeth differs from each other. To confirm this parameter, users will do duplicate training experiments. It is an easy task in comparison with motor imagery training. Meanwhile, bandpass filtered EEG data is extracted discriminative feature by well-known RCSP[8]. In Bagging, similar test will be held for 5 times. In the end, a "Winner-takes-all" strategy will determine the result as most classifiers do.

3. ONLINE AND OFF-LINE EXPERIMENTS

Based on Bagging RCSP, we did off-line and online experiments. The main difference is the source of EEG data.

3.1. Off-line experiment

Off-line experiment data comes from BCI competition III IVa[13]. In this data set, five healthy subjects were attended. Two classes visual cues denoting the following 2 motor imageries {(L) left hand, (F) foot}were displayed for 3.5s[13][14]. During the experiment, sampling rates is 100Hz. According to the competition, a training and testing set was available for each experimenter, and every set contains 140 trials for each class. Because this data set aims to test algorithm in small training sets, it provides 168, 224, 84, 56 and 28 trials for training of each subject respectively. Rest trials are for testing.

3.2. Online experiment

Ulteriorly, we did online experiments based on the real-time system in Section II. Three males and one female attended this experiment. Before playing "catch the apple" game, they were asked to complete calibration task to tune the model parameters (Fig. 5 illustrates the paradigm of a calibration trial). At the beginning, screen keeps blank. From 2 to 4s, a fixation cross appears in the screen. From 4 to 6s, a left or right arrow shows with a beep suggesting experimenter imagine her/his left or right hand movement according to the cue. After calibration trials, four attendants starting the game introduced in Section II. Score will increase by 1point as a reward when the character catches one apple. We recorded the final score of every experimenter.

4. RESULT AND DISCUSSION

From the article of RCSP[8], it shows classification accuracy has a positive correlation with number of training sample. However, the large scale training sample will increase the time and space complexity, which confines its practical application. Most importantly, accuracy is not

Table 2. Performance in online system

Result of real-time system		
subject	**Number of trials**	**score**
A	50	35
B	50	33
C	50	33
D	50	36

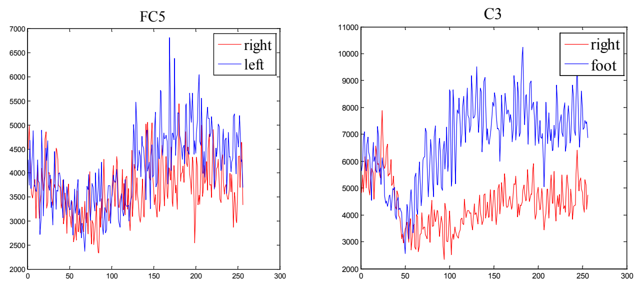


Fig.6. Spectrogram of subject A and al EEG. The data of left spectrogram comes from our experiment, while the right is from the BCI competition III.

enhanced so much when the training scale reaches the threshold(see in Fig. 6). To be specific, when the generic training trials aggrandize from 40 to 120, accuracy only improves by 1.9% in average. Different from RCSP, we did not introduce much others' training samples to estimate the covariance matrix. On the contrary, dividing the large generic training trial into small packages, and choosing data by Bagging to predict result is a sensible method. Result of the off-line experiment shows in Table 1.On the one hand, it compares the accuracies of the testing data sets for traditional CSP, RCSP and Bagging RCSP and other mainstream methods. Based on RCSP, Bagging RCSP overwhelmingly outperforms traditional CSP with no doubt. Meanwhile, in comparision with RCSP, the average improvement by 3-6% also certifies its benefits. On the other hand, consuming time to work out the result for 840 testing trials stays steadily when employing Bagging RCSP or RCSP. However, it increases so dreadfully in FERCSP that baffles its development in practical. CSP and other derived algorithm like RCSP utilize adequately the covariance information. Meanwhile, feature representation has aroused wide concern in other filed, such as feature representation in object detection[16], introduction of the new feature in image retrieval[17],and adoption of feature selection to speed up the real-time performance[18]. This is our future work to do.

Table II reveals the experimental results in the online system. The satisfying score demonstrates it is a rewarding system. In fact, manipulating the reality by a simple EEG sampling device is significant, especially for handicapped man. As an attendant, it is relatively easy to control the role's walk state by gritting teeth for me. However, the difficult thing is yet the direction control by motor imageries. We plot the power spectra of raw EEG(see in Fig.6). As we can see from the spectra, the latter is more easily discriminated. For my part, there are two main reasons: 1)the number of electrodes. Data for BCI competition III are sampled from the 118 channels, but our sampling device only has 14 channels; 2)application environment. We test the online system in the nature environment, which leads to the lower SNR. As we stressed in the beginning, the objective of this paper is to present an applied BCI system based on Bagging RCSP.

5. CONCLUSION

RCSP is demonstrated to be an effective method in BCI, and this paper introduces a framework of Bagging RCSP, which can deal with the complexity problem of noise and artifact since the large generic training scale. Bagging RCSP is tested on dataset of BCI competition III and our approach improves the classification result by 3-6% compared with RCSP. More importantly, a real-time BCI system designed based on Bagging RCSP works availably. Therefore, the proposed online system and algorithm are promising in practical.

ACKNOWLEDGEMENTS

The authors would like to thank the reviewers for their comments. This research was supported by the National Science and Technology Support Program under Grant No. 2013BAK02B04 and Initiative Scientific Research Program of Tsinghua University under Grant No. 20141081253.

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