상상 움직임에 대한 실시간 뇌전도 뇌 컴퓨터 상호작용, 큐 없는 상상 움직임에서의 뇌 신호 분류

Real-time BCI for imagery movement and Classification for uncued EEG signal

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Abstract Brain Computer Interface (BCI) is a communication pathway between devices (computers) and human brain. It treats brain signals in real-time basis and discriminates some information of what human brain is doing. In this work, we develop a EEG BCI system using a feature extraction such as common spatial pattern (CSP) and a classifier using Fisher linear discriminant analysis (FLDA). Two-class EEG motor imagery movement datasets with both cued and uncued are tested to verify its feasibility.

핵심어: Brain Computer Interface, motor imagery movement, Common spatial pattern, Fisher linear discriminant analysis, EEG

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1. Introduction

Brain Computer Interface (BCI) is a systematic way to communicate between digital devices and human brain. It has been initiated with intention to provide severely paralyzed people with some controlled convenience. Mostly EEG (electroencephalography) based BCI system has been developed since EEG is fully noninvasive and cheap to get real-time data. In general, BCI system consists of a feature extraction and classification. Feature extraction is a way to extract some underst-andable or discriminable information from real-time EEG data. Classification is to figure out which brain activities (left or right movement) extracted feature tells.

In this work, we try to implement real-time EEG based BCI system extracting special feature by common spatial pattern analysis and classifying two class brain activities by Fisher linear discriminant analysis.

2. Methods

2.1 Data description

We collected two different datasets for the real-time imagery movement from healthy subjects. For one dataset, we used 32-channel EEG system (Neuromedic WEEG-32 system), and acquired real-time EEG dataset at 256 Hz. The other dataset was got from Berlin-BCI (BBCI) group. It is a EEG dataset (dataset1 : motor imagery, uncued classifier application) among four different datasets used for BCI competition IV [4]. It consists of normal data(1a, 1b, 1f, and 1g) and artificial data(1c, 1d, and 1e).

Detailed experimental paradigms for both datasets are explained in Section 3.

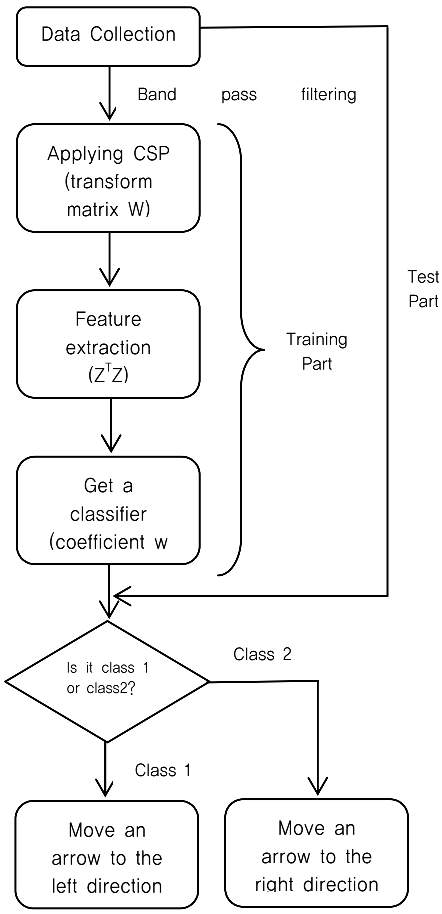
2.2 Common Spatial Pattern (CSP)

Among many methods of feature extraction, CSP method is applied. CSP is a kind of spatial filter which generates common spatial patterns from two different class spatial covariance matrices. It requires to solve generalized eigenvalue problems to get spatial filters and spatial patterns [1-2]. It is very useful feature extraction to discriminate two classes.

2.2 Fisher Linear Discriminant Analysis (FLDA)

Fisher Linear Discriminant Analysis (FLDA) is classifying easily classes through maximization of ratio of the variance between the classes to the variance within the classes. We applied FLDA to classify CSP transformed features into two classes [3].

3. Experiment

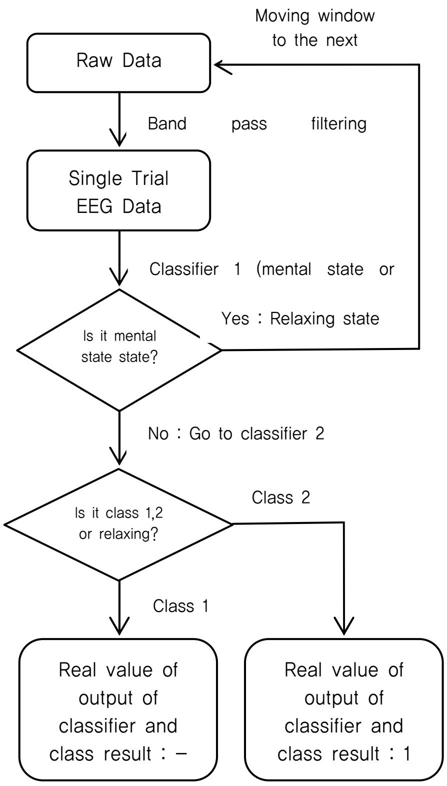


⟨Fig.1 Flow chart of data processing for experiment 1⟩

3.1 Experiment 1

We implemented real-time EEG based BCI for imagery movement (left/right hand). Firstly, we collected the EEG data during 5 sessions. For each session, we collected 40 EEG spatiotemporal data, whose class is generated randomly (left: 20 / right: 20). At initial stage blank screen is displayed and arrow (arrow gives an instruction which hand subject should imagine to move) shows up from 1s to 5s. On arrow direction shows up, spatiotemporal EEG signal is recorded as text format (ascii type). Cue (time when arrow starts to show up) is recorded. This process is repeated until 40 times are tried for each session. Between sessions, a couple of minutes rest is given. After acquiring total of 200 data, band-pass (8Hz 50Hz) filtering is done, and then CSP features are extracted. As a training data, 160 data among them were used to generate a classifier. Remaining 40 datasets were used to test how well the classifier is working.

After training sessions, we implemented the real-time test similar to the training session. Only difference between training session and test session is that in the real-time test, one ball is added at the center of the screen and it is moved to the left or right direction after imagery movement. If the imagery movement is correct, the ball moves same direction, otherwise it moves to the opposite direction.



〈Fig.2 Flow chart of data processing for experiment 2〉

3.2 Experiment 2

Another left/right hand imagery movement 59-channel EEG datasets were obtained from BCI competition Ⅳ. It is called 'Dataset 1 <motor imagery, uncued classifier application>'. During runs, arrows pointing left, right were presented as visual cues on a computer screen. Cues were displayed for a period of 4 seconds during which the subject was instructed to perform the cued motor imagery task. These periods were interleaved with 2 seconds of blank screen and 2 seconds with a fixation cross shown in the center of the screen. The fixation cross was superimposed on the cues, i.e. it was shown for 6 seconds. These data sets are provided with complete marker information.

For testing dataset, the motor imagery tasks were cued by soft acoustic stimuli (words *left*, *right*) for periods of varying length between 1.5 and 8 seconds. The end of the motor imagery period was indicated by the word *stop*. Intermitting periods had also a varying duration of 1.5 to 8 seconds. More detailed information is referred to [4]. We note that for training dataset cue information is given, but it is not given for testing dataset.

To analyze this data, we band-pass filtered between 8Hz and 30 Hz. We determined to classify EEG signal of duration 7 seconds starting 1 second after onset of stimulation (right/left instruction). To classify uncued testing dataset, we propose two subsequent classification procedures, as illustrated in Figure 2. First classifier is classifying whether ongoing signal is in mental state or not. For this purpose, we used data of 4 seconds long starting the current time point. For second classifier, we determined to use EEG signal of duration 7 seconds starting 1 second after onset of stimulation (right/left instruction).

4. Result

4.1 Experiment 1 – cued case

Five different mental states (from two subjects) were tested. Following table (Table 1) is the result of the two healthy subjects, Sun and BB. In the case of BB and BB-1, these are consecutive sessions allowing some amount of rest time.

Subject	Time	Trial	Success Rate (%)
Sun	Morning	50	84
Sun-1	Morning	50	96
Sun-2	Evening	50	78
Sun-3	Evening	50	62
BB	Morning	50	92
BB-1	Morning	50	70

〈Table.1 Result of Real-time BCI〉

Interestingly, morning time shows far better performance than evening time. It is true morning time is easier to do good and uniform concentration. We believe that BCI performance has significant effect on the mental fatigue. For the better performance, subjects need much rest before the experiment.

4.2 Experiment 2 – uncued case

We tabulated two classifiers success rates for comparison purpose over 7 kinds of datasets in Table 2. These results were generated from training data, whose cue and class information is known already. Overall, first classifier (mental state or not) tends to classify well between non-mental and mental state. Naturally, its success rate has great influence on the success rate of the second classifier to classify class 1, class 2 or relaxing.

Index	Size of Training data	Classifier 1 Is it mental state?	Classifier 2 Is it class 1, 2or relaxing?
1a	200	92.5	83.5
1b	200	81.5	65.5
1c	199	91.9858	65.8291
1d	199	96.4824	78.8945
1e	199	80.402	68.3417
1f	200	85	72.5
1g	200	79	69

〈Table.2 Success rate of Uncued dataset〉

For testing dataset (it is posted after competition), the performance is tested by mean square error (MSE) with respect to the target value (-1 : motor imagery class1, 0 : relax and 1 : motor imagery class2) during a given period. Continuous data from 1 second after the starting cue to the time the stopping cue is given are considered to be evaluated. Both empirical datasets (1a, 1b, 1f, and 1g) and artificial datasets (1c, 1d, and 1e) are tested. These results are shown in Table 3 and 4. The first column is an averaged value of results of each dataset.

MSE	1a	1b	1f	1g
0.972	1.10	1.08	0.84	0.86

〈Table.3 Result of empirical test datasets〉

MSE	1c	1d	1e
0.768	0.80	0.71	0.79

〈Table.4 Result of artificial test datasets〉

It is interesting that artificial datasets yields slightly better performance. There is no clear clue on this matter, which is under investigation.

5. Conclusion

We implemented our own EEG based BCI system under 32-channel EEG system (Neuromedic WEEG-32 system) and tested our classifier for datasets from Berlin-BCI group. CSP and FLDA combined classifier seems to be working reasonably even it has some room to be improved.

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