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Implementation of a Brain-Computer Interface Based on Three States of Motor Imagery

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Abstract—**A motor imagery based brain-computer interface (BCI) translates the subject's motor intention into a control signal through real-time detection of characteristic EEG spatial distributions corresponding to motor imagination of different body parts. In this paper, we implemented a three-class BCI manipulated through imagination of left hand, right hand and foot movements, inducing different spatial patterns of event-related desynchronization (ERD) on mu rhythms over the sensory-motor cortex. A two-step training approach was proposed including consecutive steps of online adaptive training and offline training. Then, the optimized parameters and classifiers were utilized for online control. This paradigm facilitated three directional movement controls which could be easily applied to help the motion-disabled to operate a wheelchair. The average online and offline classification accuracy on five subjects was 79.48% and 85.00% respectively, promoting the three-class motor imagery based BCI a promising means to realize brain control of a mobile device.**

Keywords—**brain-computer interface, motor imagery, event-related desynchronization**

I. Introduction

In recent years, brain-computer interface (BCI) systems based on classifying single trial EEGs during motor imagery have developed rapidly [1],[2]. The physiological studies on motor imagery indicate that the spatial distribution of EEG differs between different imagined movements, e.g. motor imagination of hand and foot. Brain activities at mu (8-12Hz) and beta (18-26Hz) rhythms display specific areas of event-related desynchronization (ERD) corresponding to each imagery state [3]. Also, lateral readiness potential (LRP), which is a slowly decreasing potential, can be recorded with the maximum amplitude over the motor cortex contralateral to the involved hand movements, whereas the readiness potential preceding a foot movement shows no lateralization [4].

ERD/ERS has a higher frequency band than LRP. Therefore, it is more robust and of a better signal-to-noise ratio than LRP in scalp recorded EEG signals which may be contaminated by low-frequency artifacts, e.g. eye blink. Most of the current motor imagery based BCIs are based on characteristic ERD/ERS spatial distributions corresponding to different motor imagery states. The first motor imagery based BCI was developed by Pfurtscheller *et al*. and was based upon the detection of EEG power changes caused by ERD/ERS of mu and beta rhythms during imagination of left and right hand movements [5]. Another motor imagery based approach proposed by Wolpaw *et al*. was to train the users to regulate the amplitude of mu and beta rhythms to realize 2-D control of cursor movement [6]. Two linear equations were used to transform the sum and the difference of EEG power over left and right motor areas into vertical and horizontal movement.

Motor imagery BCIs are mainly focused on two-class classification of motor imagination patterns [7]. When the number of brain patterns increases, great difficulties in both aspects on signal processing and machine learning algorithms stand out. In the multi-class paradigm, the classification accuracy will be decreased due to the interference of the new brain states, which may be unreliable and make the subject confused during online user training. To obtain useful information which can be fit for discriminating the new patterns, the method of feature selection has to be reconsidered. Besides, the design of the multi-class classifier also plays an important role in improving the classification accuracy.

In this study, three states of motor imagery were employed to implement a multi-class BCI. Considering the reliable spatial distributions of ERD/ERS in both primary sensory-motor cortex areas, imagination of motor activity including left hand, right hand and foot were considered the detectable brain patterns. We designed a straightforward online feedback paradigm, where real-time visual feedback was presented to indicate the controls of three directional movements, i.e. left hand, right hand and foot denote moving left, right, and forward respectively.

II. Methods

A. Data Acquisition

Five right-handed volunteers (three males and two females, 22-27 years old) participated in the study. They were chosen from the subjects who could successfully fulfill two-class online BCI control in our previous studies (4-7 hours of online training) [8]. The recording was made using a BioSemi ActiveTwo system. 32 EEG channels were measured at positions involving the primary motor area (M1) and the

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supplementary motor area (SMA) (see Fig.1). Electromyogram (EMG) recording was omitted due to the recognized finding that EMG signals show low correlations with the imagery tasks on well-trained subjects [6]. Signals were sampled at 256Hz and preprocessed by a 50Hz notch filter and a 4-35Hz band-pass filter.

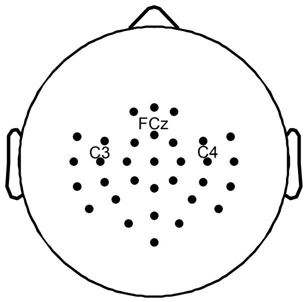

Fig.1 Electrode positions of the 32 channels in the experiment. C3/C4 and FCz electrodes in the 10-20 systems are involved to record EEG signals over M1 and SMA areas.

B. Online Feedback Paradigm

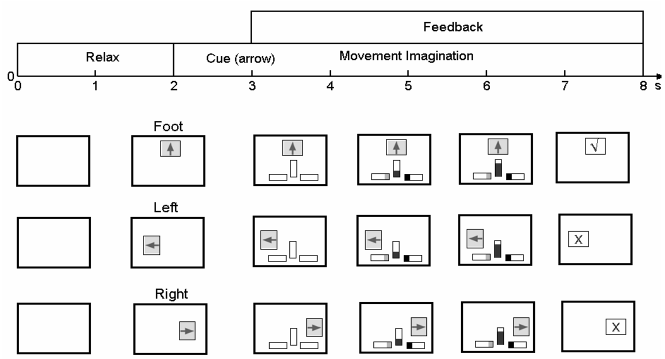

Fig.2 Online feedback paradigm of the three-class motor imagery tasks. Three examples are the tasks corresponding to foot, left hand and right hand imagination respectively. The progress bars provide real-time visual feedback.

Fig. 2 shows the paradigm of online BCI training with visual feedback. The "left hand", "right hand" and "foot" movement imagination were designated to control three directional movements, i.e. left, right, and upward respectively. The subject sat comfortably in an armchair, opposite to a computer screen for displaying the visual feedback. The duration of each trial was 8 seconds. During the first 2 seconds, while the screen was blank, the subject was in the "relax" state. At second 2, a visual cue (arrow) was presented in the screen, indicating the imagery task to be performed. The arrow pointing left, right, and upward indicated the imagination of left hand, right hand, and foot movement respectively. At second 3, three progress bars with different colors started to increase simultaneously from three different directions. The value of each bar was determined by the accumulated classification results and it was updated eight times per second (every 125ms). For example, if the current classification result is "foot", then the "up" bar will increase one step and the values of the other two bars are retained. The features extracted for classification were band-pass power of mu rhythms on left and right primary motor areas (C3 and C4 electrodes). At second 8, a true or false mark appeared to indicate the final result of the trial through calculating the maximum value of the three progress bars, and the subject was asked to relax and wait for the next task. The experiment consisted of 2 or 4 sessions and each session consisted of 90 trials (30 trials per class). The dataset comprising 360 or 180 trials (120 or 60 trials per class) was used for further offline analysis.

C. Multi-step training and controlling procedures

1) Online feedback training

Linear discriminant analysis (LDA) was used to classify the band-pass power features on C3/C4 electrodes referenced to FCz [9]. A linear classifier was defined by a normal vector $\boldsymbol{w}$ and an offset b as:

$$y = \text{sign}(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b) \quad (1)$$

where $\boldsymbol{x}$ was the feature vector. $\boldsymbol{w}$ and b were determined by Fisher discriminant analysis (FDA). The three-class classification was solved by combining three binary LDA discriminant functions:

$$\begin{aligned} &\boldsymbol{x}(t) = [P_{\mathrm{C3}}(t)\ \ P_{\mathrm{C4}}(t)]^{\mathrm{T}} \\ &y_i(t) = \text{sgn}(\boldsymbol{w}_i{}^{\mathrm{T}}\boldsymbol{x}(t) + b_i), i = 1-3 \end{aligned} \quad (2)$$

where $P_{\mathrm{C3}}(t)$ and $P_{\mathrm{C4}}(t)$ are values of the average power in nearest 1s time window on C3 and C4. Each LDA was trained to discriminate two different motor imagery states. The decision rules are listed in Table I. Two combinations were not classified, and the remaining six combinations were designated to the three motor imagery states respectively.

TABLE I
DECISION RULES OF CLASSIFYING THE THREE MOTOR IMAGERY STATES THROUGH COMBINING THE THREE LDA CLASSIFIERS

Left vs Right	Left vs Foot	Right vs Foot	Decision
+1	+1	-1	Left
+1	+1	+1	Left
-1	+1	+1	Right
-1	-1	+1	Right
+1	-1	-1	Foot
-1	-1	-1	Foot
+1	-1	+1	None
-1	+1	-1	None

An adaptive approach was used to update the LDA classifiers trial by trial. The initial normal vector $\boldsymbol{w}_i^{\mathrm{T}}$ of the classifiers were selected as [+1 -1], [0 -1], and [-1 0] (corresponding to the three LDA classifiers in Table I) based on the ERD distributions. They were expected to recognize the imagery states through extracting the power changes of mu rhythms caused by contralateral distribution of ERD during left/right hand imagery, but bilateral power distribution duringfoot imagery over M1 areas [3]. The initial b was set to zero. When the number of samples reached 5 trials per class, the adaptive training began. Three LDA were updated trial by trial, gradually improving the generalization

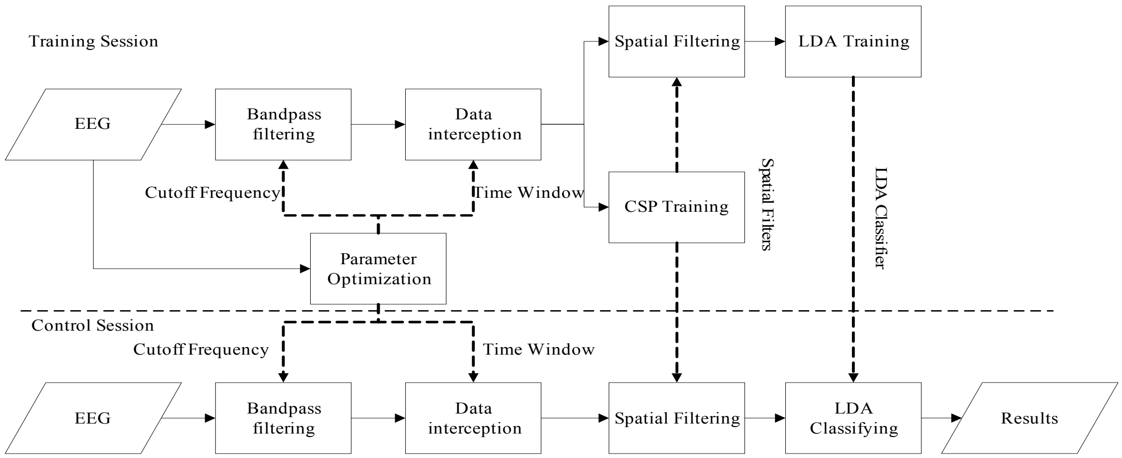

Fig.3 Flowchart of offline training and online controlling in the motor imagery based BCI.

ability of the classifiers along with the increase of the training samples. This co-adaptation manner can speed up the user training and system calibration in an online BCI due to simultaneous cooperation of brain and machine.

2) Offline training and online control

To improve the classification accuracy, we used the common spatial patterns (CSP) method to improve the signal-to-noise ratio of the mu rhythm through extracting the task related EEG components. The main idea of CSP is to use a linear transform to project the multi-channel EEG data into low-dimensional spatial subspace with a projection matrix, each row of which consists of the weights corresponding to each channel. This transformation can maximize the variance of two-class signal matrices. The algorithm is based on the simultaneous diagonalization of the covariance matrices of both classes [10].

The EEG signals under two tasks A and B can be modeled as the combination of task-related components specific to each task and non-task components common to both tasks. The aim of the CSP method was to design two spatial filters ($\boldsymbol{SF}_A$ and $\boldsymbol{SF}_B$), which led to the estimations of task-related source activities ($\boldsymbol{S}_A$ and $\boldsymbol{S}_B$) corresponding to two tasks respectively. Then, spatial filtering was performed to eliminate the common components and extract the task-related components. $\boldsymbol{S}_A$ and $\boldsymbol{S}_B$ were estimated by $\boldsymbol{S}_A = \boldsymbol{SF}_A \cdot X$ and $\boldsymbol{S}_B = \boldsymbol{SF}_B \cdot X$, where X was a data matrix of preprocessed multi-channel EEG. After spatial filtering, the feature vector was defined as:

$$f = [\log(\mathrm{var}(\boldsymbol{S}_A)) \quad \log(\mathrm{var}(\boldsymbol{S}_B))]\,. \tag{3}$$

The CSP multi-class extensions have been considered in [11]. Three different CSP algorithms were presented based on one-versus-one, one-versus-rest, and approximate simultaneous diagonalization methods. Similar to the design of binary classifiers, the one-versus-one method was employed in our system to estimate the task related source activities as the input of the binary LDA classifiers. It can be easily understood and with less unclassified samples compared with the one-versus-rest method. The design of spatial filters through approximate simultaneous diagonalization costs large amount of calculation and the selection of the CSP patterns is more difficult than the two-class version.

As illustrated in Fig.3, before online BCI control, the CSP based training procedure was performed to determine the parameters for data preprocessing, the CSP spatial filters, and the LDA classifiers. A sliding window method was integrated to optimize the frequency band and the time window for data preprocessing in the procedure of joint feature extraction and classification. The accuracy was estimated by a 10×10-fold cross-validation. The optimized parameters, CSP filters, and LDA classifiers were used to implement the online BCI control and ensured a more robust performance compared with the online training procedure. In our BCI demo, two subjects have successfully played a robot-cup soccer game through controlling the movement of two robot dogs (one as the goalkeeper and the other as the forward).

III. Results

The EEG power spectra of one subject under three different motor imagery states are displayed in Fig.4. It presents a significant contralateral dominance during hand movement imagery. The C3 electrode has a much lower power during right hand imagery than left hand. On the contrary, the lower power is corresponding to left hand imagery on electrode C4. In contrast to hand movements, foot imagination shows a high power on both hemispheres.

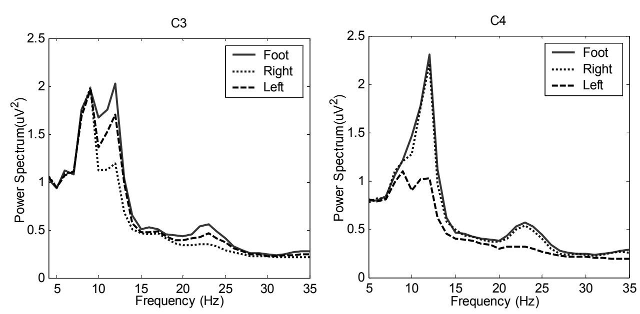

Fig.4 Average power spectra on C3/C4 electrodes for one subject. For each class, 120 trials were used for averaging.

TABLE II

CLASSIFICATION ACCURACIES CORRESPONDING TO ONLINE AND OFFLINE CLASSIFICATION ON FIVE SUBJECTS

Subjects	Trials	Pass band	Time window	Offline accuracy				Online accuracy
				Left vs Right	Left vs Foot	Right vs Foot	Total	
SJH	360	10-35Hz	2.5-8s	99.33±0.44%	99.61±0.27%	97.94±0.59%	98.11±0.70%	94.00%
WW	360	13-15Hz	2.5-7.5s	99.83±0.35%	96.92±0.97%	98.92±0.40%	97.56±1.23%	94.67%
ZYJ	180	9-15Hz	2.5-7s	98.20±2.57%	82.40±4.88%	90.60±5.17%	80.13±4.68%	74.71%
FL	180	10-28Hz	2.5-6s	96.33±1.72%	83.67±2.92%	85.67±2.63%	77.00±2.82%	68.00%
ZD	180	10-15Hz	2.5-7.5s	95.17±1.83%	78.17±5.06%	71.83±8.66%	72.22±4.32%	66.00%
Mean	—	—	—	97.77%	88.15%	88.99%	85.00%	79.48%

Fig.5 shows the probability of the online feedback (the normalized values of the three progress bars) under the three different tasks. The maximum value of the three progress bars was consistent with the task. For example, during foot imagination, the "upward" bar had a much higher value than the "left" and "right" bars; therefore, for most foot imagery tasks, the final decision was correct although some errors may occur during the feedback period (from 3s to 8s).

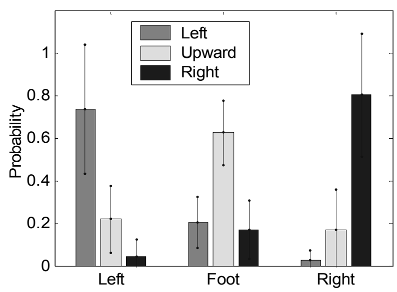

Fig.5 Probability of the three progress bars corresponding to the three motor imagery tasks for one subject (statistical results over 120 trials per class).

Table II lists the parameters for data preprocessing and classification results of all the subjects. The pass band and the time window are subject-specific parameters which can significantly improve the classification performance. Average accuracy derived from online and offline analysis was 79.48% and 85.00% respectively. For subjects SJH and WW, no significant difference existed between the classification results of the three binary classifiers and a high accuracy was obtained for three-class classification. For the other three subjects, the foot task was difficult to be recognized and the three-class accuracy was much lower than the accuracy of classifying left and right hand movements. It may be caused by less training of the foot imagination, because all the subjects did more training sessions of hand movement in previous studies of two-class motor imagery classification [8]. The average offline accuracy was 5.52% higher than the online result due to the employment of parameter optimization and the CSP algorithm applied to multi-channel EEG data.

IV. CONCLUSION

An online three-class motor imagery based BCI has been implemented in our study. An adaptive approach was used during the online training procedure, and expected to reduce the training time through simultaneous brain-machine co-adaptation. To improve the classification accuracy, offline data analysis was performed before online BCI control. A significant performance gain was achieved after using the CSP based algorithm. In our future work, online training based on the multi-class CSP algorithm will be tested and further facilitate user training in the motor imagery based BCI.

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