An Algorithm for Idle-State Detection and Continuous Classifier Design in Motor-Imagery-Based BCI

Yu Huang, Qiang Wu, Xu Lei, Ping Yang, Peng Xu, and De-Zhong Yao

***Abstract*—The development of asynchronous brain-computer interface (BCI) based on motor imagery (MI) poses the research in algorithms for detecting the nontask states (i.e., idle state) and the design of continuous classifiers that classify continuously incoming electroencephalogram (EEG) samples. An algorithm is proposed in this paper which integrates two two-class classifiers to detect idle state and utilizes a sliding window to achieve continuous outputs. The common spatial pattern (CSP) algorithm is used to extract features of EEG signals and the linear support vector machine (SVM) is utilized to serve as classifier. The algorithm is applied on dataset IVb of BCI competition III, with a resulting mean square error of 0.66. The result indicates that the proposed algorithm is feasible in the first step of the development of asynchronous systems.**

***Index Terms*—Brain-computer interface competition, common spatial pattern, continuous classifier, idle state, motor imagery, support vector machine.**

1. Introduction

Many different kinds of neurophysiologic disorders, e.g. amyotrophic lateral sclerosis, brainstem stroke, brain or spinal cord injury, etc., can disrupt the normal pathways through which the brain communicates with the environment. The most severe patients who suffer from these diseases may even lose all voluntary muscle control, unable to interact with their surroundings[1]. Over the past decades, a novel technology called brain-computer interface (BCI) has been proposed and developed to offer the possibilities of communications for these patients. Briefly speaking, a BCI is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles[1]. The BCI system itself is able to understand the intention of the patients and translate it into commands controlling external assistive devices.

Current BCIs based on electroencephalograph (EEG) signals could be categorized into two types: dependent BCIs and independent BCIs. The former depend on external stimuli (e.g. flash) to the users while the latter are completely controlled by the users' intent. One of the independent systems is based on motor imagery (MI), in which the subject sends commands to the computer by performing imagined movements (e.g., imagined hand movement). At present, most researchers of MI-based BCIs focus on the discrimination of different MI tasks, which correspond to different controlling commands, and they have developed some systems in which the users could control the cursor on the computer screen through their imagined movements at a fairly high accuracy[2]-[4]. However, these systems are synchronous, i.e., the subjects perform motor imagery according to the cues presented by the system and the algorithms applied only work on each MI task, ignoring the EEG signals when the subjects stay in the non-task periods. When it comes to the practical BCI systems out of the laboratory, the first problem needs to be solved is how to effectively detect these non-task states (i.e., idle state) of the users, since users do not want to operate the system when they stay in idle state. Therefore, the research and development of algorithms which can not only discriminate different MI tasks but also detect the idle state is crucial to the improvement of MI-based BCIs.

This contribution attempts to design an idle-state detecting algorithm for MI-based BCIs. The proposed algorithm, which was applied to dataset IVb of BCI Competition III, is described in Section 2. The results and conclusions are given in Section 3 and Section 4, respectively.

2. Methodology

2.1 Data Description

BCI Competitions are held to promote research and communication in algorithms and signal processing techniques among BCI researchers around the world. Through an objective criterion, the effectiveness and robustness of a variety of data-analysis approaches could be evaluated and

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compared with one another. The raw EEG data provided to the competitors were recorded in the top BCI laboratory in the world, including two parts: one with labels (training data) and the other one without labels (testing data). Requirements for the competitors are to apply different algorithms on the testing data to predict its labels based on the information obtained from the training data. The predicted labels are evaluated by the organizers and a ranking of applied approaches on each dataset will be given as the result of the competition.

Dataset IVb of BCI Competition III was recorded from one healthy subject. The two classes of motor imagery were left hand and right foot. In the training block (consisted of three sessions, 70 trials for each session), arrows pointing left or down were presented as visual cues on a computer screen, indicating left hand or right foot imagery, respectively. Cues were displayed for a period of 3.5 s during which the subject was instructed to perform the cued motor imagery task. These periods were interleaved by non-task periods of random length, 1.75 s to 2.25 s. In the testing block (consisted of four sessions), the motor imagery tasks and the relax task, which simulates the idle state, were cued by soft acoustic stimuli (words left, foot and relax) for periods of varying length between 1.5 s and 8 s. The end of the task period was indicated by the word stop. Intermitting non-task periods had also a random duration of 1.75 s to 2.25 s. The EEG was recorded using a 118-channel Ag/AgCl electrode cap with sampling rate of 1000 Hz[5].

Competitors of this dataset are required to submit their predicted labels for every sample point of the testing data, i.e., ideally, −1 for left hand, 1 for right foot and 0 for relax (idle state). As mentioned in Section 1, most of current algorithms on MI-based BCIs are evaluating classification of MI tasks (i.e., trials), where each trial corresponds to a fixed length of EEG signals and pays no attention to the idle state. As to this dataset, however, it is unknown to the competitors that at what intervals the subject is in a defined mental state, and it is required that the classifier must export a value between −1 and 1 for incoming EEG sample continuously. Therefore, the algorithm has to analyze the data in both task and idle state, with the main difficulty that how to separate those sample points when the subjects were in the idle state from those when they performed MI tasks.

2.2 Preparation for Feature Extraction

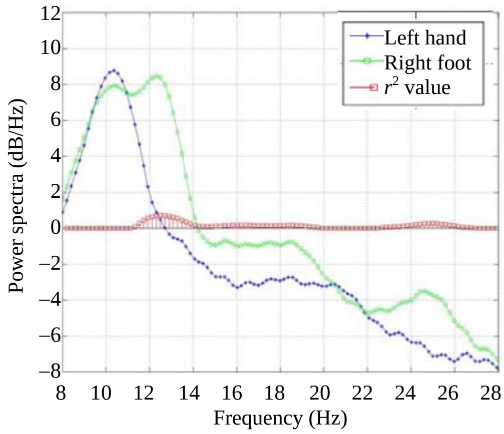
Studies show that when performing motor imagery, the mu (8 Hz to 12 Hz) and beta (18 Hz to 26 Hz) rhythms of EEG are found to reveal event-related desynchronization/synchronization (ERD/ERS), a power decreases/increases in that frequency band of the ongoing EEG, over sensorimotor cortex[6]. Such a neurophysiologic phenomenon is the fundamental for the discrimination of different MI tasks.

To extract the features of different tasks based on this phenomenon, the common spatial pattern (CSP) algorithm, which is a highly successful method proposed by Ramoser *et al.*[7], was used as the approach for feature extraction. In the preparation for CSP, the training data were down-sampled to 100 Hz and re-referenced to common average reference. Subject-specific frequency bands, temporal windows and channel combinations were then selected based on the r^2-values obtained from

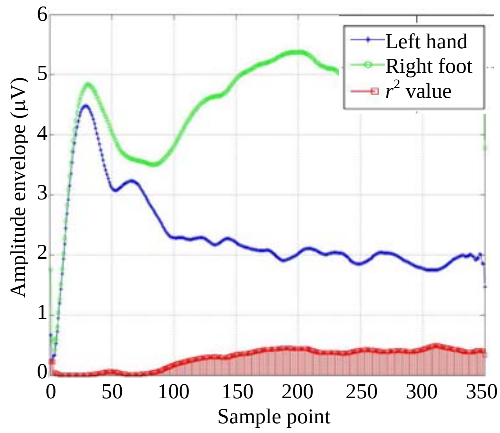
$$r^2 = \left[\frac{\sqrt{N_1 N_2}}{N_1 + N_2} \frac{\text{mean}(X_1) - \text{mean}(X_2)}{\text{std}(X_1 \cup X_2)} \right]^2 \tag{1}$$

where X_1 and X_2 are the features of hand task and foot task, respectively, and N_1 and N_2 are the numbers of samples used for calculating the features. The r^2-values reflect the separability of X_1 and X_2.

Fig. 1 shows the class-wise averaged power spectra, amplitude envelope and corresponding r^2-values calculated from the training data on channel C3. The r^2-values were used to choose manually the frequency band and temporal window with the most significant separability.



(a)



(b)

Fig. 1. The calculated results from the training data on channel C3:

(a) the class-wise averaged power spectra and (b) the class-wise averaged amplitude envelope of the chosen frequency band.

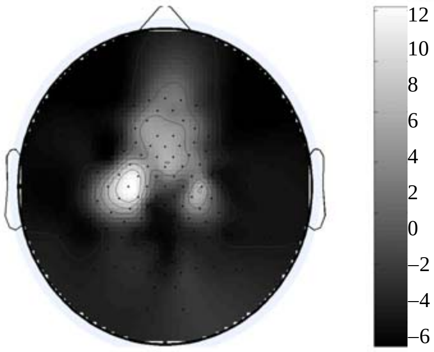


Fig. 2. The r^2-values of averaged power spectra calculated on each electrode.

From Fig. 1 (a), we selected 12 Hz to 14 Hz as the frequency band for the CSP algorithm. The averaged amplitude envelope of this frequency band is shown in Fig. 1 (b), from which the temporal window including the 71st to 350th samples for each trial could be selected. In addition, Fig. 2 shows the r^2-values of averaged power spectra calculated on each electrode. It is obvious that the most significant ERD/ERS phenomenon occurs around channels C3 and C4, i.e., the sensorimotor cortex. A 15×15-fold cross-validation was performed on the training data for each channel combination from the maximum r^2-value to the minimum r^2-value and an optimal channel combination could be determined for the following CSP algorithm.

2.3 Feature Extraction

The down-sampled and re-referenced training data were filtered through the chosen frequency band and set as input to the CSP algorithm. Generally speaking, the goal of CSP algorithm is to design spatial filters that lead to new temporal signals whose variances are optimal for the discrimination of two populations of EEG related to two MI tasks[7]. It is based on the simultaneously diagonalization of two covariance matrices.

Let $\mathbf{X}$ denote the single-trial EEG data, $\mathbf{X}=\mathbf{NW}$, where $\mathbf{N}$ is the selected channel combination and $\mathbf{W}$ is the chosen temporal window. The normalized spatial covariance matrix of $\mathbf{X}$ could be obtained from

$$\mathbf{C}=\frac{\mathbf{XX}^T}{\mathrm{tr}(\mathbf{XX}^T)} \tag{2}$$

where T denotes the transpose operator and $\mathrm{tr}(\mathbf{A})$ is the sum of the diagonal elements of $\mathbf{A}$, and the spatial covariance matrix of each class is calculated as $\mathbf{C}_1$ and $\mathbf{C}_2$ by averaging across the trials of corresponding class. The sum covariance matrix $\mathbf{C}_{\mathrm{sum}}$ is factorized into the product of eigenvectors and eigenvalues,

$$\mathbf{C}_{\mathrm{sum}}=\mathbf{C}_1+\mathbf{C}_2=\mathbf{U}_0\mathbf{\Sigma}\mathbf{U}_0^T\,. \tag{3}$$

The eigenvalues are sorted in descending order in $\mathbf{\Sigma}$. The whitening transformation matrix is then formed as

$$\mathbf{P}=\sqrt{\mathbf{\Sigma}^{-1}}\times\mathbf{U}_0^T\,. \tag{4}$$

If $\mathbf{C}_1$ and $\mathbf{C}_2$ are transformed as

$$\mathbf{Q}_1=\mathbf{PC}_1\mathbf{P}^T,\quad \mathbf{Q}_2=\mathbf{PC}_2\mathbf{P}^T, \tag{5}$$

then $\mathbf{Q}_1$ and $\mathbf{Q}_2$ share common eigenvectors, i.e., if

$$\mathbf{Q}_1=\mathbf{U\Sigma}_1\mathbf{U}^T \tag{6}$$

Then

$$\mathbf{Q}_2=\mathbf{U\Sigma}_2\mathbf{U}^T \tag{7}$$

$$\mathbf{\Sigma}_1+\mathbf{\Sigma}_2=\mathbf{I} \tag{8}$$

where $\mathbf{I}$ is the identity matrix. Since the sum of two corresponding eigenvalues is always one, the eigenvector with largest eigenvalue for $\mathbf{Q}_2$ has smallest eigenvalue for $\mathbf{Q}_1$ and vice versa[7]. This property makes $\mathbf{U}$ useful for separating variances in the two matrices $\mathbf{C}_1$ and $\mathbf{C}_2$. Taking out the first m_1 columns of $\mathbf{U}$ as $\mathbf{U}_1$ and the last m_2 columns of $\mathbf{U}$ as $\mathbf{U}_2$, we can construct the spatial filters as

$$\mathbf{F}_1=\mathbf{U}_1{}^T\mathbf{P},\quad \mathbf{F}_2=\mathbf{U}_2{}^T\mathbf{P} \tag{9}$$

for hand task and foot task, respectively[8].

Applying the spatial filters to the single-trial EEG data $\mathbf{X}$, we obtain the task-related components as

$$\mathbf{S}_1=\mathbf{F}_1\mathbf{X},\quad \mathbf{S}_2=\mathbf{F}_2\mathbf{X} \tag{10}$$

and the feature vectors of this trial as

$$\mathbf{f}_{1,i}=\log\left(\mathrm{var}(\mathbf{S}_{1,i})\right),\quad i=1,2,\cdots,m_1 \tag{11}$$

$$\mathbf{f}_{2,i}=\log\left(\mathrm{var}(\mathbf{S}_{2,i})\right),\quad i=1,2,\cdots,m_2 \tag{12}$$

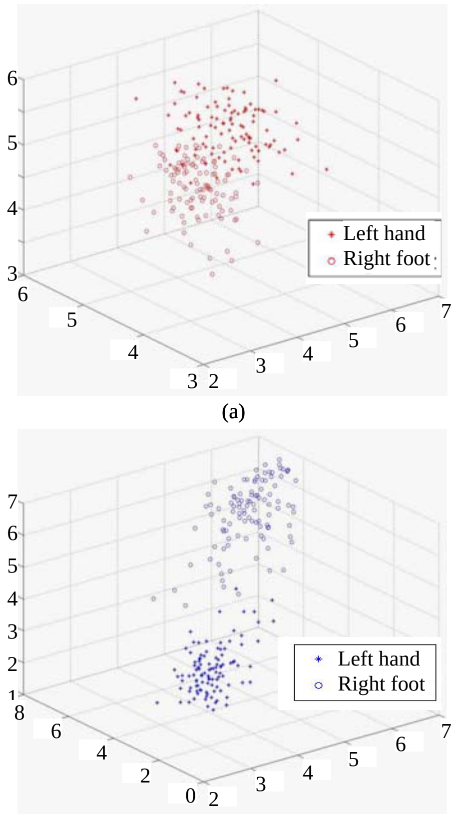
where $\mathbf{S}_{1,i}/\mathbf{S}_{2,i}$ represents the ith row vector of $\mathbf{S}_1/\mathbf{S}_2$. The log-transformation approximates the data to normal distribution[8].

According to the procedure described above, the feature vectors of training data can be extracted by setting $m_1=m_2=3$, and the distribution of these vectors can be obtained, as shown in Fig. 3.

Obviously, no matter filtered by $\mathbf{F}_1$ or $\mathbf{F}_2$, the trials of hand task and foot task can be separated fairly well. As a consequence, two classifiers are to be trained on the corresponding feature vectors obtained from $\mathbf{F}_1$ and $\mathbf{F}_2$, respectively.

2.4 Feature Classification

The principle of classification between hand task and foot task is based on the average of the outputs of the two trained classifiers. Since the features are well separable, we simply chose linear classifiers. Two linear support vector machines (SVM) were trained using the feature vectors with hand task labelled as −1 and foot task labelled as +1[9].



(b)

Fig. 3. The distribution of feature vectors obtained from $\mathbf{F}_1$ (a) and $\mathbf{F}_2$ (b), where asterisk and circle stand for hand task and foot task, respectively. In the figure, the three axes represent the three components of feature vectors, which indicate the variances of spatial filtered EEG signals.

As shown in Fig. 3, the two decision hyperplanes represented by the classifiers split the feature space into two parts, one with negative outputs of the classifiers and the other with positive outputs. With the constructed SVMs, an incoming feature vector without label could be fed, leading to two outputs, whose absolute values are the distances of the vector to the corresponding decision hyperplane, and whose signs indicate which side the vector locates to the corresponding hyperplane. The average of the two outputs determines the class of the unlabelled feature vector, i.e., hand task if it is negative and foot task if positive. To examine the performance of linear SVM, a 15×15-fold cross-validation was performed on the training data and the classification result was (99.52 ± 1.84)% (mean ± std.).

The result proves that the linear SVMs behave well enough on the training data and thus they can be adopted as the classifiers for the testing data.

2.5 Classification on the Testing Data

As for the testing data, two tough problems need to be solved: 1) the detection of idle states, and 2) the determination of temporal intervals of every task and idle state, in which the classifier must give an output at each sample point.

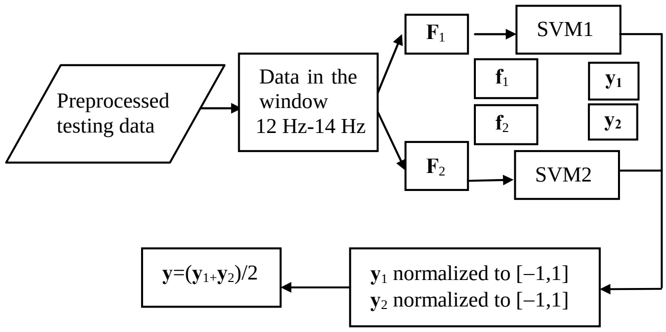


Fig. 4. Flowchart of Step 1.

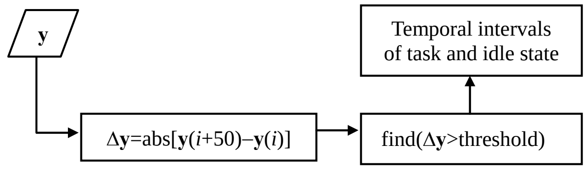


Fig. 5. Flowchart of Step 2.

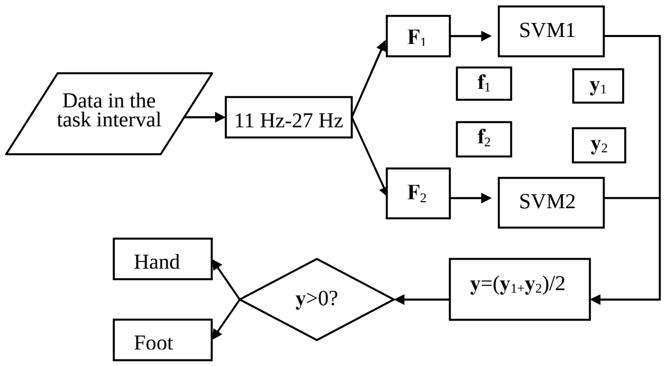


Fig. 6. Flowchart of Step 3.

To address these two problems, a flow including 3 steps was proposed as follows.

Step 1: a sliding window including 150 samples moved in temporal order on the testing data, sample-by-sample, to obtain the features ($\mathbf{f}_1, \mathbf{f}_2$) of the preprocessed testing data. The features were classified via the SVMs, resulting in two outputs ($\mathbf{y}_1, \mathbf{y}_2$), which were normalized to the interval of [−1, 1] and averaged, as shown in Fig. 4.

Step 2: a difference sequence ($\Delta\mathbf{y}$) of the output of Step 1 was calculated every 50 points, and a threshold was determined to detect those samples at which the mental states of the subject changed, leading to the temporal intervals of task and idle state, as shown in Fig. 5.

Step 3: Similar to Step 1, but with slightly different parameters, those data in the task intervals were processed to obtain a value (**y**). The task was classified as hand if the corresponding **y** was negative and foot if it was positive, as shown in Fig. 6.

Step 1 serves to detect the idle states which correspond to those averaged outputs (**y**) congregating around 0. The output of each sample is determined by its previous 150 samples, i.e., the samples under the sliding window. Based on the analysis in Section 2.4, the classifiers in Fig. 4 would result in one of the following outputs (Table 1) for each sample in ideal conditions[8].

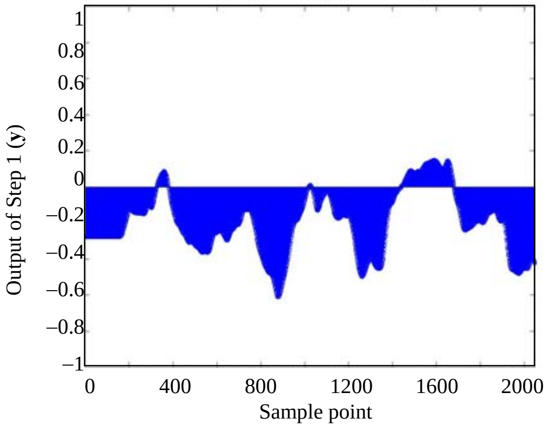


Fig. 7. The value of **y** at each sample point obtained from Step 1. Note that the figure only shows about 2000 samples out of the testing data.

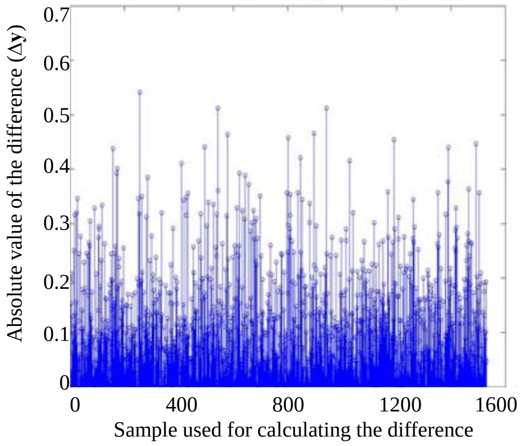


Fig. 8. The difference sequence of **y**.

Table 1: The combination of outputs in Step 1

Feature task	Normalized y_1	Normalized y_2	$y=(y_1+y_2)/2$
Hand	–1	–1	–1
Foot	1	1	1
Idle state	–1 or 1	1 or –1	0

Step 2 is a strategy to determine the temporal intervals of tasks and idle states. With the outputs ($\mathbf{y}$) of Step 1, what is needed to do next is to find those samples with **y** around 0. Since it is difficult to set two thresholds directly separating **y** to –1, 0, and 1, an indirect way is adopted to investigate the difference of **y** at two neighboring samples, because large difference of **y** may indicate the switch of mental states of the subjects. Our investigation shows that the value of **y** varies gradually along the temporal axis, as shown in Fig. 7. Therefore, the difference is calculated every 50 points as

$$\Delta\mathbf{y} = \text{abs}\left[\mathbf{y}(i+50) - \mathbf{y}(i)\right] \tag{13}$$

where $\mathbf{y}(i)$ is the value of **y** at sample *i*, rather than every two points, to increase the effectiveness of such a strategy.

Fig. 8 shows the plot of the difference sequence ($\Delta\mathbf{y}$). Note that we only consider the absolute value of the difference. A threshold needs to be determined to detect the point at which the mental states change. In our approach, the threshold is set in the guarantee that the number of points between two neighboring detected samples is in the range of [150, 800], the temporal interval of one specific mental state in the experiments. With the threshold determined, those samples between two neighboring detected points are considered as an interval of a specific mental state.

Step 3 classifies the data in the task intervals into hand and foot. Note that a broader frequency band is selected according to Fig. 1 (a) due to the result in [10] that a broad frequency band including both mu and beta rhythms is better for classifying two MI tasks (e.g., left hand vs. right foot) compared to a narrow band.

3. Results and Discussion

The result of dataset IVb is evaluated by mean square error (MSE) criterion as

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{t}_i - \mathbf{y}_i)^2 \tag{14}$$

where N is the number of samples in the testing data, $\mathbf{t}_i$ and $\mathbf{y}_i$ denote the true label and the output of the classifiers of each sample point, respectively. Note that in the calculation of MSE, the outputs during intermitting periods are ignored. An MSE of 0.66 is obtained through our algorithm.

In addition, other two criteria for evaluating the outputs with more direct meaning are applied. One is the total classification accuracy (TCA):

$$\text{TCA} = \frac{N_c}{N_t} \tag{15}$$

where N_t is the total number of samples in the output and N_c is the number of samples correctly classified. Since there are three classes (left hand, right foot, and idle state), the TCA will be 33.33% if the classification is made by chance. Our methods result in a TCA of 46.22%. Besides, the other is the percentage of detected idle state (PI):

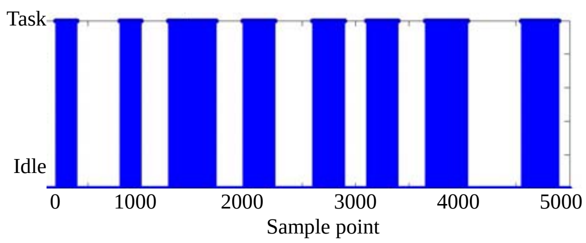
$$\text{PI} = \frac{N_d}{N_{\text{idle}}} \tag{16}$$

where N_{idle} is the total number of idle-state samples and N_d is the number of correctly detected idle-state samples. A PI of 48.73% is obtained via our approach, i.e., nearly half of the idle states are detected.

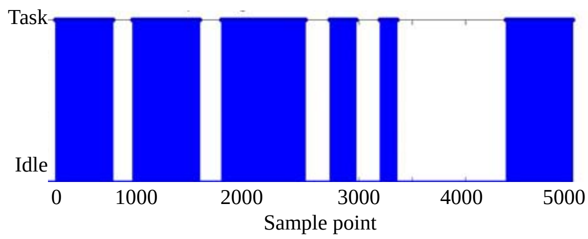
In the final results of BCI Competition III, there is only one submission to this dataset and thus no comparison among different algorithms could be made. Nevertheless, our algorithm does make an effort in the most difficult field of the research of current MI-based BCIs, i.e., the detection of idle state and the design of continuous classifier. As an attempt, our methods need to be improved in at least two directions as follows.

1) The improvement on the classifiers. Due to the non-stationarity of EEG signals, the distributions of the extracted features may shift or even rotate in the feature space. As a consequence, a classifier with good performance on the training data may behave badly on the testing data. In our approach, the normalizations in Step 1 overcome the problem of feature shifting, yet neglecting the possibility of feature rotation, which is a main source of classification errors. Investigations on the design of robust classifiers which are not sensitive to rotation of feature vectors will be carried out in our future work.

2) A better and more effective method of temporal segmentation. Fig. 9 shows the predicted and true task intervals in the experiment. The samples under the color bars belong to a certain task, e.g., hand task, while the samples out of the color bars belong to the idle states. It is clear from the figure that the result of temporal segmentation on the testing data is not consistent with the true distribution of task intervals, which is the main source of errors in classification in Step 3. One reason for such a disaccord may come from Step 2, in which we simply chose the difference of classifier outputs at different samples with a margin of 50 points as a tool for detecting switches of mental states, without considering the classification errors at the samples used for calculating the difference. Therefore, a more effective method for the segmentation of task intervals should be thoroughly investigated.



(a)



(b)

Fig. 9. The task intervals in the experiment: (a) predicted task intervals and (b) true task intervals. Note that the figure only shows about 5000 samples out of the testing data.

4. Conclusions

In this paper, an algorithm for idle-state detection in MI-based BCIs and in the sense of continuous classifier is introduced and applied to dataset IVb of BCI Competition III. To detect the idle state, the proposed algorithm constructs two two-class classifiers and utilizes the average of their outputs. On the other hand, a sliding window is used to predict the label of the sample locating at the end of the window, resulting in continuous outputs of the classifiers.

Current trend in the development of MI-based BCIs is practical systems that are asynchronous. To this end, future BCI systems must integrate idle-state detecting algorithms and continuous classifiers that analyze continuously incoming EEG samples. Dataset IVb of BCI Competition III poses the challenges in both the two aspects mentioned above, and it is an effective tool in the beginning of the research and development for asynchronous systems. Moreover, the absence of various algorithms dealing with such a dataset indicates that much more efforts are needed in the research towards asynchronous systems, not only offline but also online. Although the analysis is conducted offline in this paper, it is easy to be integrated into online systems.

Our future work will be focused on developing new idle-state detecting mechanisms and the design of continuous classifiers in online system.

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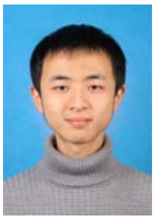

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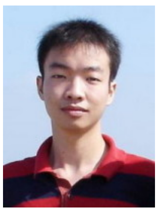

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