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Multi-class Filter Bank Common Spatial Pattern for Four-Class Motor Imagery BCI

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Abstract— **This paper investigates the classification of multi-class motor imagery for electroencephalogram (EEG)-based Brain-Computer Interface (BCI) using the Filter Bank Common Spatial Pattern (FBCSP) algorithm. The FBCSP algorithm classifies EEG measurements from features constructed using subject-specific temporal-spatial filters. However, the FBCSP algorithm is limited to binary-class motor imagery. Hence, this paper proposes 3 approaches of multi-class extension to the FBCSP algorithm: One-versus-Rest, Pair-Wise and Divide-and-Conquer. These approaches decompose the multi-class problem into several binary-class problems. The study is conducted on the BCI Competition IV dataset IIa, which comprises single-trial EEG data from 9 subjects performing 4-class motor imagery of left-hand, right-hand, foot and tongue actions. The results showed that the multi-class FBCSP algorithm could extract features that matched neurophysiological knowledge, and yielded the best performance on the evaluation data compared to other international submissions.**

I. Introduction

THE use of Brain-Computer Interfaces (BCI) in real-world applications is limited by low bit-transfer rates. To enhance the information gain from multi-channel scalp electroencephalogram (EEG) recordings, an approach is to instruct the subject to perform tasks that generate multiple discriminative brain states rather than just two brain states [1]. These multiple brain states could be induced through motor imagery whereby the subject imagines performing a movement from the first-person perspective without actually executing it [2]. As illustrated in the human homunculus [3], and functional Magnetic Resonance Imaging studies on finger, toe and tongue imagery [2], different body parts have a spatially ordered layout in the primary motor cortex. Hence, spatially discriminable patterns of EEG signals [4] are discernable for multi-class motor imagery BCI (MI-BCI).

Studies have been performed to assess signal processing and machine learning techniques for discriminating multiple brain-states in MI-BCI. One approach is the multi-class extension of the Common Spatial Pattern (CSP) algorithm, which has shown effectiveness in calculating spatial filters that maximize the variance between 2 conditions such as left-hand and right-hand motor imagery [5]. Various multi-class approaches to extend the CSP algorithm have been reported, such as the Pair-Wise approach [6], the One-Versus-Rest approach [4], the Simultaneous Diagonalization approach [4] and Information Theoretic Feature Extraction (ITFE) approach [7]. These approaches were investigated on 3 to 4 classes of motor imagery data from the hands, foot or tongue.

However, a caveat of the CSP algorithm is the selection of specific frequency bands of the EEG data. Although a wideband of 8-30Hz was suggested [5], evidence showed that selecting subject-specific frequency bands could yield an improvement in the recognition rate of MI-BCI [8]. To address the problem of selecting the subject-specific frequency band for the CSP algorithm, the Filter Bank Common Spatial Pattern (FBCSP) algorithm was proposed for MI-BCI. The FBCSP algorithm classifies single-trial EEG based on selected features computed from subject-specific temporal-spatial filters. The performance of the FBCSP algorithm has shown encouraging results on in-house data from 8 healthy subjects and 35 hemiparatic stroke patients, as well as publicly available data from the BCI Competition III dataset IVa [9] and the BCI Competition IV dataset IIb [10].

However, the FBCSP algorithm is limited to binary-class motor imagery. Hence this paper proposes 3 approaches of multi-class extension to the FBCSP algorithm: the One-Versus-Rest (OVR) approach, the Pair-wise (PW) approach, and the Divide-and-Conquer (DC) approach. As the CSP algorithm used in FBCSP was originally designed for binary-class problems, these 3 approaches decompose the multi-class problem into several binary-class problems. The performance of these 3 approaches are investigated on 4-class single-trial EEG data from the BCI Competition IV dataset IIa whereby 9 subjects performed left-hand, right-hand, foot or tongue motor imagery.

The remainder of this paper is organized as follows: Section II describes the FBCSP algorithm. Section III describes the 3 proposed approaches of the multi-class extension. Section IV discusses the results on the BCI Competition IV dataset IIa and analyzes the performance of the proposed approaches.

II. Filter Bank Common Spatial Pattern (FBCSP)

The FBCSP algorithm was developed to address the selection of the subject-specific frequency band for the CSP algorithm [9]. The FBCSP algorithm, shown in Fig. 1,

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comprises 4 stages that perform an autonomous selection of subject-specific temporal-spatial discriminative EEG characteristics for 2-class MI-BCI.

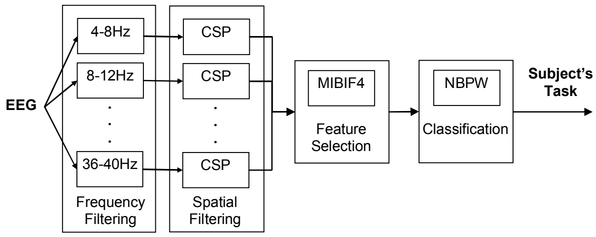


Fig. 1: Architecture of the FBCSP algorithm for two-class motor imagery EEG data

The first stage of FBCSP performs frequency filtering using a Chebyshev Type II filter bank that decomposes the EEG measurements into 9 multiple pass-bands 4-8Hz, 8-12Hz … 36-40Hz. The second stage performs spatial filtering by linearly transforming the EEG data using the CSP algorithm to the following feature vector for the i^{th} trial,

$$\mathbf{x}_i = \left[\mathbf{cf}_1, \mathbf{cf}_2, \ldots, \mathbf{cf}_9\right], \tag{1}$$

where $\mathbf{cf}_b \in \mathbb{R}^{2m}$ denotes the m=2 pairs of CSP features for the b^{th} band-pass filtered EEG measurements, $\mathbf{x}_i \in \mathbb{R}^{1\times(9*2m)}$.

The third stage performs feature selection of the extracted features using the Mutual Information Best Individual Features (MIBIF) algorithm [9]. This algorithm selects the best k=4 features sorted by mutual information with the class label in descending order. Since CSP features are paired, the corresponding CSP features which come in pairs with the selected k features are also selected.

The fourth stage performs classification using the Naïve Bayes Parzen Window (NBPW) Classifier, where the classification rule is given as

$$\omega = \underset{\omega=1,2}{\arg\max}\, p\left(\omega \mid \mathbf{x}\right), \tag{2}$$

where $p(\omega|\mathbf{x})$ denotes posterior probability of the class being ω=1,2, given the random trial $\mathbf{x} = \left[x_1, x_2, \ldots x_d\right]$ and d denotes the number of selected features from the third stage.

For further details on the FBCSP algorithm, the reader is referred to [9].

III. Proposed Approaches of Multi-Class FCBSP

In the following subsections, it is assumed that the classes $\omega, \omega' \in \{1,2,3,4\}$ where $\{1,2,3,4\}$ represent the left, right, foot and tongue motor imagery for 4-class MI-BCI.

A. One-Versus-Rest (OVR) Approach

The proposed OVR approach [4] computes CSP features that discriminates each class from all the other classes. However, instead of performing a Linear Discriminant Analysis multi-class classification on all the projected signals [4], the proposed OVR approach uses multiple binary NBPW classifiers. Hence 4 OVR classifiers are required for the 4-class MI-BCI. The classification rule of the NBPW classifier is extended from (2) to

$$\omega = \underset{\omega=1,2,3,4}{\arg\max}\, p_{\text{OVR}}\left(\omega \mid \mathbf{x}\right), \tag{3}$$

where $p_{\text{OVR}}\left(\omega \mid \mathbf{x}\right)$ is the probability of classifying $\mathbf{x}$ between ω=1,2,3,4 and $\omega'=\{1,2,3,4\}\backslash\omega$; and \ denotes the set theoretic difference operation.

B. Pair-wise (PW) Approach

The proposed Pair-Wise (PW) approach [6],[11] computes CSP features that discriminates every pair of classes. Hence 4(4−1)/2=6 binary classifiers are required for the 4-class MI-BCI. The classification rule of the NBPW classifier is thus extended from (2) to a majority voting scheme based on the predicted class labels from the binary classifiers using

$$\omega = \underset{\omega=1,2,3,4}{\arg\max}\left[\sum_{\substack{\omega'=1\\ \omega'\neq\omega}}^{4}\left|p_{\text{PW}}\left(\omega \mid \mathbf{x}\right) > p_{\text{PW}}\left(\omega' \mid \mathbf{x}\right)\right|\right], \tag{4}$$

where $p_{\text{PW}}\left(\omega \mid \mathbf{x}\right)$ is the probability of classifying $\mathbf{x}$ between ω =1,2,3,4 and $\omega' \neq \omega$; and the absolute operator $\left|\cdot\right|$ here returns 1 if it is true and 0 otherwise.

C. Divide-and-Conquer Approach

The proposed Divide-and-Conquer (DC) approach [12],[13] is similar to the OVR approach, but adopts a tree-based classifier approach. Hence 4-1=3 binary classifiers are required for the 4-class MI-BCI. The classification rule of the NBPW classifier is thus extended from (2) to

$$\omega = \min\left[\underset{\omega=1,2,\ldots,4}{\arg\max}\left|\left(p_{\text{DC}}\left(\omega \mid \mathbf{x}\right) > p_{\text{DC}}\left(\omega' \mid \mathbf{x}\right) \mid \omega' > \omega\right)\right|\right], \tag{5}$$

where $p_{\text{DC}}\left(\omega \mid \mathbf{x}\right)$ is the probability of classifying $\mathbf{x}$ between ω =1,2,3,4 and $\omega' > \omega$; and $p\left(\omega' \mid \mathbf{x}\right) = 0$ if $\omega'=\varnothing$, and the absolute operator $\left|\cdot\right|$ here returns 1 if it is true and 0 otherwise. The order of classification was pre-determined by 10×10-fold cross-validations results of each class versus all the other classes.

IV. Experimental Results

The multi-class FBCSP algorithm was evaluated on the 4-class single-trial motor imagery data of BCI Competition IV dataset IIa [14], of which 1 training session and 1 evaluation session of EEG data from 9 subjects are provided. Each session comprised of 288 single trials. Fig. 2 shows how each trial of motor imagery is conducted. At the start of each trial, a fixation cross is displayed on the computer screen for 2s. Subsequently, a visual cue instructs the subject to perform left-hand, right-hand, foot or tongue motor imagery for 4s, followed by a break period before the next trial.

To train the multi-class FBCSP algorithm, the segment of 0.5s to 2.5s of EEG data after the onset of the visual cue was used. The choice of m for the CSP algorithm in equation (1) was set to 2.

The performance of the proposed approaches of multi-class extension to the FBCSP algorithm was evaluated on the training data using 10×10-fold cross-validations, and on the independent evaluation data. The performance measure used was the Kappa value, computed from the BIOSIG toolbox http://biosig.sourceforge.net/. The performance was evaluated on the entire single-trial EEG from the onset of the fixation cross using a sliding window of 2s.

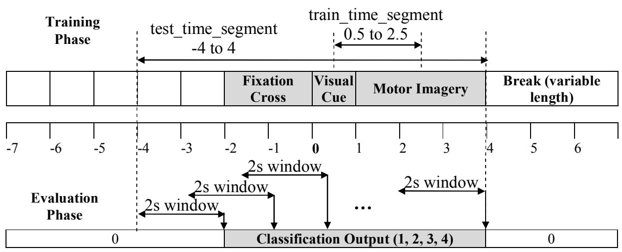


Fig. 2: The FBCSP algorithm is trained on *train_time_segment* and evaluated on the entire segment of the single trial EEG data in *test_time_segment*.

A. Multi-class FBCSP Performance Evaluation

The 10×10-fold cross-validations results on the training data are shown in terms of mean validation Kappa value in Table 1. The independent test set performance of the FBCSP algorithm on the evaluation data in terms of mean Kappa values is shown in Table 2, where the best results for each subject are also shaded. The OVR approach was submitted to BCI Competition IV for dataset IIa and achieved the best mean Kappa value relative to the 2nd and 3rd placed submissions, denoted respectively in Table 2.

TABLE 1
10×10-FOLD CROSS-VALIDATIONS OF THE MULTI-CLASS FBCSP ALGORITHM

	Mean Kappa values on validation set for each subject									
	1	2	3	4	5	6	7	8	9	AVG
OVR	0.77	0.48	0.83	0.49	0.61	0.35	0.84	0.81	0.78	0.66
PW	0.78	0.45	0.86	0.47	0.63	0.33	0.85	0.79	0.78	0.66
DC	0.73	0.44	0.81	0.42	0.63	0.36	0.83	0.78	0.76	0.64

TABLE 2
INDEPENDENT TEST SET EVALUATION OF MULTI-CLASS FBCSP ALGORITHM

	Mean Kappa values on evaluation data for each subject									
	1	2	3	4	5	6	7	8	9	AVG
OVR	0.68	0.42	0.75	0.48	0.4	0.27	0.77	0.75	0.61	0.57
PW	0.78	0.41	0.75	0.53	0.42	0.19	0.8	0.74	0.54	0.57
DC	0.71	0.38	0.66	0.47	0.44	0.24	0.73	0.75	0.56	0.55
2nd	0.69	0.34	0.71	0.44	0.16	0.21	0.66	0.73	0.69	0.52
3rd	0.38	0.18	0.48	0.33	0.07	0.14	0.29	0.49	0.44	0.31

Statistical analysis using one-way ANOVA found no significant differences among the 3 proposed approaches (p-value = 0.96 for both tables). The OVR approach and the PW approach yielded the highest mean Kappa value. However the OVR approach is less computationally intensive since 4 OVR classifiers are used compared to 6 PW classifiers. Statistical analysis using the paired t-test shows the performance of the OVR approach is better relative to the 2nd placed submission (p-value = 0.0475)

B. Analysis of the OVR Approach on Evaluation Data

Fig. 3 shows the time course of the Kappa values for the OVR approach. The maximum classification accuracy is achieved around 3s after the visual cue onset. This is consistent with the 0.5s to 2.5s of training data after the visual cue onset, used to train the multi-class FBCSP.

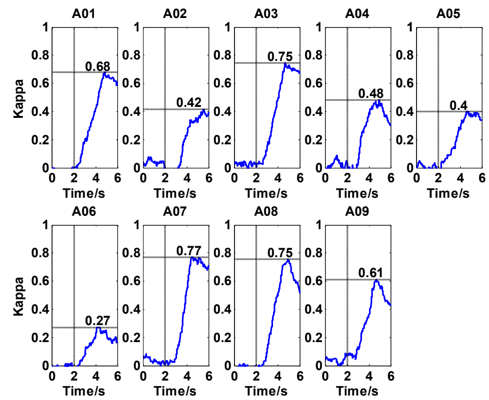
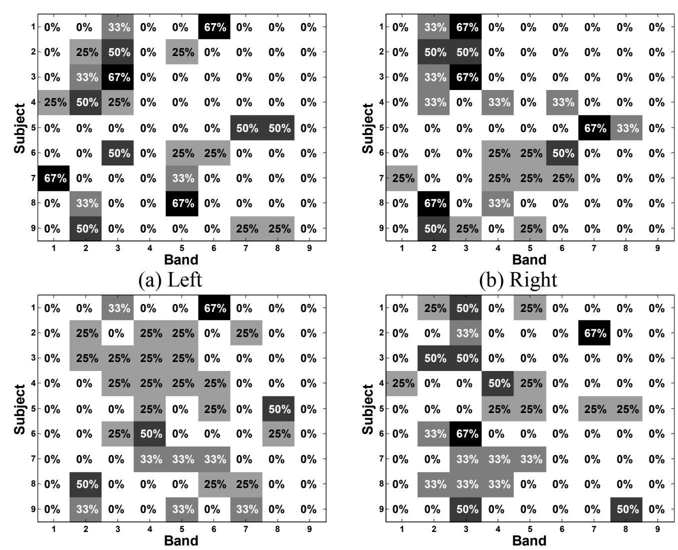


Fig. 3: Time course of Kappa value for the evaluation data, using the OVR approach to the multi-class FBCSP algorithm. The onset of the fixation cross and visual cue are set to 0s and 2s respectively.

The frequency bands from which the MIBIF algorithm selects the discriminative CSP features are shown as histogram percentages in Fig. 4 for the 4 OVR classifiers and for all subjects. A darker level of shading was displayed for a frequency band which is frequently chosen. Examining Subject 7, the selected features were mostly from the 12-28Hz bands that encompass the *alpha* / *mu* band and the *beta* band. These frequency bands have been shown to exhibit Event-Related Desynchronization / Synchronization (ERD/ERS) effects during motor imagery [1],[8],[15].



(a) Left (b) Right (c) Foot (d) Tongue

Fig. 4: Histogram of features selected from specific filter bands for each classifier based on the OVR approach using all the training data. The vertical axis in each chart represents Subjects 1 to 9 from top to bottom. The horizontal axis represents the filter bands 1 to 9 from left to right.

Further analysis is performed by plotting selected spatial patterns of the CSP feature pairs from Subject 7's training data in Fig. 5. The left (right) hand motor imagery resulted in the activation of the region around the right (left) motor cortex. The foot motor imagery resulted in the activation of the region closer to the midline. For the tongue motor imagery, activation around the motor cortex was also detected. These findings were consistent with the CSP scalp topographies in [4] and the concept of the human homunculus [3] , hence these spatial patterns showed the neurophysiological plausibility of the selected CSP features.

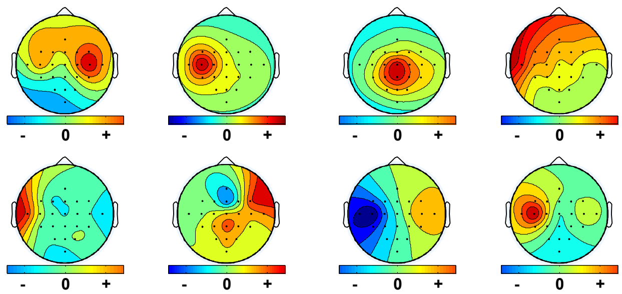


Fig. 5: Selected spatial patterns of the features for Subject 7 for each of the 4 component classifiers in the OVR approach

TABLE 3
CONFUSION MATRIX OF THE EVALUATION DATA IN PERCENTAGE AVERAGED ACROSS ALL SUBJECTS

		Predicted Class			
		Left	Right	Foot	Tongue
True Class	Left	0.75	0.15	0.04	0.06
	Right	0.10	0.79	0.06	0.05
	Foot	0.11	0.15	0.54	0.20
	Tongue	0.12	0.11	0.13	0.64

However, the spatial patterns of all the subjects were not fully consistent with neurophysiological plausibility. Studies on multi-class motor imagery showed that not all subjects exhibit ERD/ERS effects during motor imagery [16]. Hand motor imagery induced a significant ERD in all subjects, whereas foot and tongue motor imagery induced a significant ERS only in certain subjects [15]. Since the CSP algorithm is capable of extracting ERD effects [4], the FBCSP algorithm yielded relatively better performance on the hand motor imageries, compared to the tongue and foot motor imagery as shown in the confusion matrix of the evaluation data in Table 3.

V. CONCLUSION

This paper investigated the performance of 3 approaches proposed for the multi-class extension to the Filter Bank Common Spatial Pattern (FBCSP) algorithm. As the CSP algorithm in FBCSP was originally formulated for binary-class problems, these 3 proposed approaches decompose the multi-class motor imagery problem into several binary class problems. These 3 approaches were evaluated on the 4-class motor imagery data of BCI Competition IV dataset IIa. The experimental results showed no significant difference between the 3 proposed approaches. The One-versus-Rest (OVR) approach was submitted for the competition and performed the best on the evaluation data relative to the other submissions [10]. The results also showed the multi-class FBCSP algorithm could extract features whose spatial patterns matched with neurophysiological knowledge [3]. The variability in the performance of the multi-class FBCSP algorithm on the different classes of motor imagery action across all subjects could be due to the presence or absence of ERD/ERS effects in certain motor imagery actions.

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