A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain–Computer Interfaces

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***Abstract*—Event-related desynchronization/synchronization patterns during right/left motor imagery (MI) are effective features for an electroencephalogram-based brain–computer interface (BCI). As MI tasks are subject-specific, selection of subject-specific discriminative frequency components play a vital role in distinguishing these patterns. This paper proposes a new discriminative filter bank (FB) common spatial pattern algorithm to extract subject-specific FB for MI classification. The proposed method enhances the classification accuracy in BCI competition III dataset IVa and competition IV dataset IIb. Compared to the performance offered by the existing FB-based method, the proposed algorithm offers error rate reductions of 17.42% and 8.9% for BCI competition datasets III and IV, respectively.**

***Index Terms*—Brain–computer interface, electroencephalogram, motor imagery.**

I. Introduction

Brain–computer interface (BCI) is an emerging technology for paralyzed people for communicating with external world. Electroencephalogram (EEG)-based BCI translates the changes in brain signals into operative control signals. Motor imagery (MI) is the state during which the representation of a specific motor action is internally reactivated within the working memory without any overt motor output and that is governed by the principles of motor control [2]. MI creates measurable potential changes in the EEG signals termed as event-related desynchronization/synchronization (ERD/ERS) patterns. The time, frequency, and spatial nonstationarity of these patterns result in high intersubject and intrasubject variability in MI-based BCIs (MI-BCIs). One of the most effective algorithms for MI-BCI is based on common spatial pattern (CSP) technique [1], [3]. The success of CSP in BCI application greatly depends on the proper selection of subject-specific frequency bands. In the literature, common sparse spectral spatial pattern (CSSSP) [4], subband CSP (SBCSP) [5], Filter bank CSP (FBCSP) [6], and adaptive FBCSP [7] have been proposed for choosing the optimal frequency band automatically. The FBCSP [6], which won dataset IIa and IIb in BCI competition IV, uses CSP features from a set of nine fixed bandpass filters and feature selection algorithm based on mutual information to effectively choose the subject-specific features. This selection process selects features from the relevant frequency components. As the subject-specific frequency components carry distinct features, the proposed method uses a subject-specific FB selection before feature extraction to enhance the accuracy of the FBCSP framework. This paper proposes a new method to obtain subject-specific discriminative FB (DFB) instead of using fixed FB for all subjects. The following sections present the design of filters, generation of DFB, feature extraction using CSP algorithm, and classification results.

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II. Proposed Method: DFBCSP

The proposed DFBCSP system extracts subject-specific discriminative frequency bands from a set of filters, named as parent FB in the sequel. The parent FB is designed using a coefficient decimation (CD) technique [8], and it covers all frequency components in the range of 6–40 Hz. As it has been shown that EEG signals from sensorimotor cortex have the highest discriminating power between various MI tasks [9], we select EEG channels C3 and C4 in order to determine the subject-specific discriminative frequency components. Fig. 1 shows the block diagram of DFBCSP. In the band selection procedure, the parent FB filters EEG from C3 or C4 and fisher ratio of filtered EEG is used to determine the subject-specific discriminative frequency bands. Once the subject-specific frequency bands are selected, the EEG from all channels is filtered using these discriminative bands for further CSP processing. A support vector machine (SVM) classifier is used to evaluate to which class the output belongs to. Each of the EEG processing steps in the proposed method is explained in the following sections.

A. Generation of Frequency Bands Using CD Technique

The frequency bands associated with MI vary between subjects, and CD technique has the ability to obtain subbands with desired center frequencies. In our method, the parent FB is designed using CD technique for filtering the selected motor cortex EEG signals. The basic principle of CD is as follows: If every Mth coefficient of a finite impulse response filter $h(n)$ (called modal filter) is kept unchanged and all other coefficients are replaced by zeros, we get $h'(n)$, whose frequency response is a multiband response scaled by M (amplitude of decimated response will be reduced by M times) with respect to that of $h(n)$

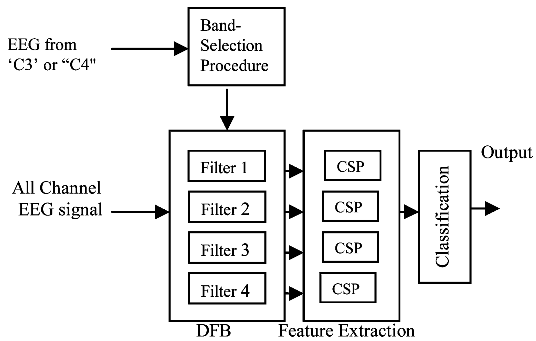


Fig. 1. Block diagram of proposed DFBCSP.

and replicas of frequency responses are introduced at integer multiples of $2\pi/M$; i.e.

$$h'(n) = h(n).c_M(n) \tag{1}$$

where

$$c_M(n) = \begin{cases} 1, & \text{for } n = kM, k = 0, 1, 2, \ldots M-1 \\ 0, & \text{otherwise.} \end{cases}$$

By changing the value of M, different numbers of frequency response replicas located at different center frequencies can be obtained. The passbands of the multiband response obtained will have identical widths as that of the modal filter. As $C_M(n)$ can be either 0 or 1, $h'(n)$ will be either $h(n)$ or 0. A decimated version of the original frequency response $h(n)$ can also be obtained using only the nonzero coefficients after discarding the in between zeros, whose passband width is M times that of the original modal filter. Thus, from the original set of coefficients of a single modal filter, frequency responses of various bandwidths and center frequencies can be generated for various values of M and k [7], [8]. Since ERD/ERS patterns have been shown to vary in the α and β bands of EEG signals [9], that is 8–30 Hz, a larger frequency range of 6–40 Hz is allowed for the proposed technique to select the discriminative bands automatically. This is because higher frequency components are successfully used in [10] for mental task classification.

B. Generation of DFB and Bandpass Filtering

The parent FB covers frequency components from 6 to 40 Hz. However, the most discriminative bands during MI vary between subjects. The FBCSP in [6] algorithm extracts CSP features from a fixed FB consisting of nine Chebyshev type II bandpass filters and a feature selection process is done before classifying the signals. Instead of using a fixed FB for all subjects, the proposed method uses a subject-specific FB to enhance the classification accuracy. In order to obtain the subject-specific DFB from the original set of bands, a discriminative spectral estimation of signals from motor cortex is used. Fisher ratio (a measure of discriminabilty between two classes of MI tasks) of spectral power from channels C3 or C4 is used to determine the most discriminative frequency bands for all subjects. For EEG patterns of right hand and foot MI, channel C3 on the contralateral hemisphere or Cz should give better discrimination. Therefore, the effectiveness of different channel selection possibilities are tested in this work: 1) single channel-C3; 2) GC3-group of channels surrounding C3; 3) LC3-Laplacian filtered C3; and 4) Cz. Also for patterns from right and left hand MI, we tested the efficacy of channels C3 and C4 also. The parent FB processes these signals and an estimate of spectral power associated with each subband is calculated using the following equation to obtain subject-specific DFB,

$$P(f_i, t) = \frac{1}{T}\sum_{n=1}^{T} x_{t,f}(n)^2. \tag{2}$$

In (2), $P(f_i, t)$ is the spectral power estimated in ith band output for the tth trial and T is the number of samples in filtered EEG signal $x_f(n)$. Thus, we obtain an $N_f \times N_t$ matrix corresponding to spectral power where N_f is the number of bands and N_t is total number of trials. Thus, each trial is associated with an estimated P value in all the frequency bands. In order to select the best informative filters, the fisher ratio, F_R, is calculated from all filter outputs from parent FB. The fisher ratio at each band output is calculated using the following equation:

$$F_R(f) = \frac{S_B}{S_W} \tag{3}$$

where $S_W = \sum_{k=1}^{C}\sum_{t=1}^{n_k}(P_t - m_k)^2$ and $S_B = \sum_{k=1}^{C} n_k(m - m_k)^2$ are the within-class variance and between-class variance, respectively, m is the total average, m_k is the average for class k, (k = 1, 2), C is the number of classes, and n_k denotes the number of trials for class k. Then filters giving highest FR values possess better discriminating power and are used for further data processing.

C. Feature Extraction Using CSP

After bandpass filtering using the DFB, EEG signal from each frequency band is applied with a CSP transformation to obtain features for classification. CSP is an effective technique for discriminating MI tasks [1], [3]. The decomposition of EEG using CSP or spatial filtering leads to a new time series, whose variances are optimal for the discrimination of two populations. The spatially filtered signal Z of a single trial EEG is given by

$$Z = WE \tag{4}$$

where E is an $N \times T$ matrix representing the raw EEG measurement data of a single trial, N is the number of channels, T is the number of samples, and W is the CSP projection matrix. The rows of W or spatial filters are designed such that the variances of first and last rows of Z give the maximum discrimination between two classes of MI tasks. Therefore, the feature vector F_p is formed from Z according to (5), where Z_p is the first and last m rows of Z, $p \in \{1 \ldots 2m\}$. The value of m is taken as 1 in the proposed DFBCSP framework,

$$F_p = \log\left[(\mathrm{var}(Z_p)) \Big/ \left(\sum_{i=1}^{2m}\mathrm{var}(Z_i)\right)\right]. \tag{5}$$

D. Classification Using SVM

SVM is a linear discriminant that maximizes the separation between two classes of MI task based on the assumption that it improves classifier's generalization ability. The CSP features extracted from DFB are used to train the SVM classifier. The

SVM model developed from the training data is used to evaluate the new EEG samples or test EEG.

III. Results and Discussions

Two publicly available datasets are explored in DFBCSP framework: BCI competition III dataset IVa [11], [12] and BCI competition IV dataset IIb [13]; we call Dataset-I and Dataset-II respectively in the sequel. Dataset-I is of right hand and foot MI and Dataset-II is of right hand and left hand MI tasks. Comparison of classification accuracies in both datasets by the proposed DFBCSP algorithm with existing FBCSP algorithm is presented.

The classification performance is evaluated in FBCSP and DFBCSP using a 10 $\times$ 10-fold cross-validation procedure. This validation procedure mixes the dataset randomly and divides into ten equally sized distinct partitions. Each partition is then used for testing, while other partitions are used for training the model. This results in ten different error rates or accuracy, which are averaged. This is the error of tenfold cross validation. To further improve the estimate, the procedure is repeated ten times and all error rates over these ten runs are again averaged [3]. The average accuracy or error rate over ten runs obtained for the test data is taken as the performance evaluation criteria, which is named as validation accuracy or validation error rate of one subject. The tuning of frequency components and SVM model are done in each fold only on the training data, which means the parameter tuning is independent from the test data used. For classification, the SVM algorithm in Bioinformatics Matlab toolbox is used with default parameters.

A. Dataset-I: Right Hand and Foot MI

Dataset-I is of right hand and foot MI tasks recorded from five subjects named "aa," "al," "av," "aw," and "ay" from 118 electrodes. As the training data in the BCI competition III dataset IVa is small, we have merged its training and test data together such that the Dataset-I consists of 280 trials of EEG measurements, 140 trials from each class of MI. Then a 10 $\times$ 10-fold cross-validation is done to analyze the performance. The data are extracted from selected electrode positions, starting from 0.5 to 2.5 s after the visual cue. The time segment selected in our work is consistent with the experiments performed in [5], [6].

As the patterns are of right hand and foot MI tasks, signals from the contra lateral channel C3, Cz and its surrounding channels are filtered to estimate the fisher ratio associated with each subband as explained in Section II-B. The single channel C3 alone offers better performance for selecting DFB, compared to a set of channels around C3, Laplacian filtered C3 and Cz. Thus, we fixed the frequency selection channel as C3 for all the five subjects in Dataset-I. After getting DFB, CSP features extracted from filtered EEG signals are given to an SVM classifier. The average validation accuracy across five subjects versus various channel selection possibilities and bandwidth of the filters are plotted in Fig. 2(a) and (b), respectively. The bandwidth of the filters is varied from 2 to 6 Hz and best results in the proposed DFBCSP scheme corresponds to a bandwidth of 4 Hz. Therefore, we fixed parent FB as a set of 12 bandpass filters of uniform bandwidth 4 Hz, covering frequency components from 6 to 40 Hz. In addition, the variation of average validation accuracies and standard deviation for 10 $\times$ 10-fold cross-validation corresponding to different number of filter passbands are shown in Fig. 2(c).

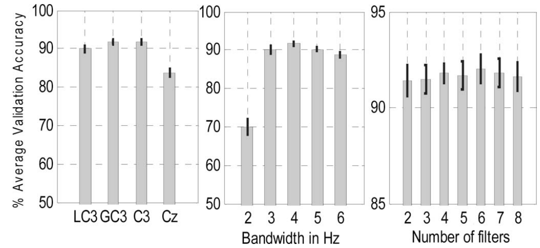
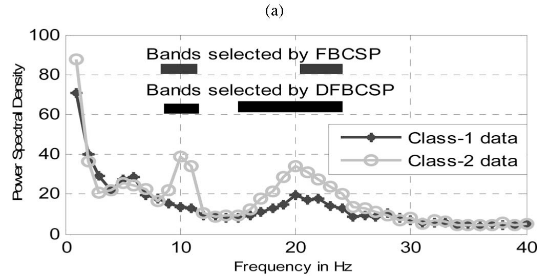


Fig. 2. (a) Average validation accuracy over five subjects in Dataset-I with Laplacian C3, group of channel around C3, C3 and Cz. (b) Average validation accuracy versus bandwidth of filters. (c) Average validation accuracy and standard deviation over five subjects versus number of filters used in DFB.

6-10Hz	8-12Hz	12-16Hz	14-18hz	18-22Hz	20-24Hz	23-27Hz	26-30Hz	28-32Hz	31-35Hz	32-36Hz	36-40Hz	
1	2	3	4	5	6	7	8	9	1	1	1	Parent FB
		1			4	2	3					'aa'
		1	4		3	2						'al'
	4		3	2	1							'av'

(a)



(b)

Fig. 3. (a) Parent and discriminative frequency bands chosen for the subjects "aa," "al," and "av" in Dataset-I using DFBCSP. The shaded portions stand for DFB for each subject. The four frequency bands in DFB are ranked according the fisher ratio values. (b) Average power spectral density plots of right hand and foot trials for subject "av" in Dataset-I. Bands chosen by Fisher analysis in proposed DFBCSP and feature selection algorithm in FBCSP are shaded accordingly.

Among various number of bands from 2 to 8, a selection of four bands in DFB gives better performance in the proposed DFBCSP scheme. The 12 frequency bands taken in the parent FB and subject-specific bands selected for three subjects in Dataset-I are shown in Fig. 3(a). The parent FB is composed of 12 frequency bands of uniform bandwidth 4 Hz, which is obtained by applying CD technique to a prototype low-pass filter of bandwidth 2 Hz. The location of the center frequencies depend on the decimation values as explained in Section II-A. The four frequency bands in DFB are ranked according to the descending order of fisher ratio values obtained. The intersubject variability of discriminative frequency components can be seen in Fig. 3(a). This corresponds to the DFB obtained from training data during the first fold of 10 $\times$ 10-fold cross-validation for the given three subjects.

In addition, the average power spectral density of two-class EEG signals recorded from C3 for subject "av" is plotted in Fig. 3(b). Frequency components with good discrimination between both classes are observed in the range of 8–12 Hz and

TABLE I
VALIDATION ERROR RATE ± STANDARD DEVIATION (%): DATASET-I

Subject	FBCSP	DFBCSP	
'aa'	6.93 ± 0.58	9.79 ± 0.56	Average Error rate reduction by the Proposed DFBCSP is **17.42%**
'al'	0.97 ± 0.24	1.32 ± 0.29	
'av'	31.00± 1.42	22.21 ± 0.99	
'aw'	4.90 ± 0.89	2.14±0.37	
'ay'	6.18 ± 0.97	5.79±0.53	
Average	**9.99 ± 0.82**	**8.25 ± 0.54**	

TABLE II
VALIDATION ERROR RATE ± STANDARD DEVIATION (%): DATASET-II

Subject	FBCSP	DFBCSP	
'B0103T'	23.50 ± 1.61	20.06 ± 1.48	Average Error rate reduction by the Proposed DFBCSP is **8.90%**
'B0203T'	43.18 ± 3.05	41.56 ± 2.89	
'B0303T'	45.06 ± 0.95	42.62 ± 1.99	
'B0403T'	0.62 ± 0.00	1.87 ± 0.00	
'B0503T'	9.56 ± 0.42	10.87 ± 1.14	
'B0603T'	20.25 ± 1.44	17.62 ± 1.17	
'B0703T'	13.50 ± 1.44	11.88 ± 0.83	
'B0803T'	11.25 ± 0.00	11.06 ± 0.93	
'B0903T'	18.12 ± 1.45	11.44 ±0.93	
Average	**20.56 ± 1.15**	**18.73± 1.26**	

15–25 Hz. From analysis, it is found that FBCSP selects features from bands 8–12 Hz and 20–24 Hz and the DFBCSP selects four bands: 8–12 Hz, 14–18 Hz, 18–22 Hz, and 20–24 Hz. Therefore, DFBCSP efficiently identifies the discriminative frequency components and offers better results. The classification accuracies for five subjects are given in Table I, where columns 2 and 3 tabulate the validation results of FBCSP [6] and our DFBCSP algorithms, respectively. From the experimental results, the proposed DFBCSP gives an error rate reduction of 17.42% compared to the FBCSP algorithm.

B. Dataset-II: Right Hand and Left Hand MI

Dataset-II has right hand and left hand MI EEG patterns recorded from three channels C3, Cz, and C4, for nine subjects, at sampling frequency 250 Hz. The names of nine subjects in Dataset-II analyzed here are "B0103T," "B0203T," "B0303T," "B0403T," "B0503T," "B0603T," "B0703T," "B0803T," and "B0903T," respectively. It is the training session 3 of BCI competition IV dataset IIb and consists of 160 trials: with 80 trials of each MI task. The effectiveness of two channel selection possibilities are analyzed by using C3 and C4 in order to discriminate right hand and left hand MI tasks. Experimental results show that the DFB selection from C4 yields better validation accuracy than using C3 in the proposed DFBCSP framework for all subjects. Table II gives the validation error rates for FBCSP and proposed DFBCSP algorithms respectively for all the nine subjects in Dataset-II. Our DFBCSP provides an error rate reduction of 8.9% compared to FBCSP. The validation accuracies for all subjects in Dataset-I and Dataset-II are plotted in Fig. 4.

IV. CONCLUSION

This paper presents a new method for selecting subject-specific DFB for the classification of MI tasks. The proposed DFBCSP method successfully replaces the feature extraction from nine filter outputs followed by a feature selection procedure in FBCSP, by DFB selection and feature extraction processes. The DFBCSP selects the subject-specific discriminative frequency bands using fisher ratio of filtered EEG signal from channels C3 or C4. The proposed method enhances the classification accuracy of BCI competition III dataset IVa and BCI competition IV dataset IIb. Preliminary results of proposed method are promising and future work includes more extensive testing on a large population of subjects as well as applying the proposed method for online adaptation.

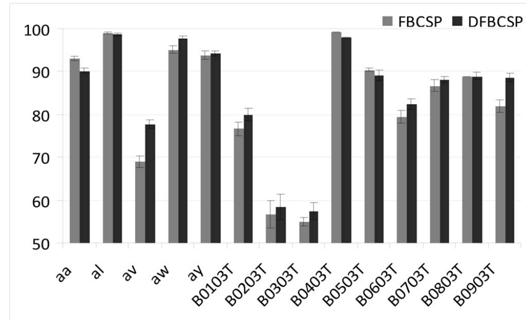


Fig. 4. Validation accuracies for all subjects in Dataset-I and Dataset-II using FBCSP and proposed DFBCSP.

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