Discriminative FilterBank Selection and EEG information Fusion for Brain Computer Interface

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Abstract—Brain Computer Interface (BCI) provides a direct communication pathway between a human and an external device. In this paper, we propose a new 'Discriminative FilterBank Common Spatial Pattern (DFBCSP)' algorithm to select the subject-specific filters automatically during training for a motor imagery based BCI. The subject-specific filters are selected using the fisher ratio values of filtered Electroencephalogram (EEG) signal. The channel 'C3' alone could give sufficient information to select the discriminative filterbank for the proposed system. We have also explored the possibility of boosting the system performance by including dynamic temporal features. Fusion of static and dynamic features in the proposed DFBCSP frame work gave an average test accuracy of 92.44%, which is significantly better than conventional filterbank based Common Spatial Pattern algorithms.

I. INTRODUCTION

EEG is one of the most common non invasive methods for obtaining brain signal. As EEG signals can be used to interpret human intentions, it provides a potential non muscular communication channel for severely disabled people. The new communication channel called Brain Computer Interface (BCI) extracts the neural information hidden in EEG signal to control external devices such as a computer, wheelchair, neuroprothesis etc. Various neurological phenomena, such as visually evoked potentials, slow cortical potentials, P300 potentials, mu and/or beta rhythms and event related (de-) synchronization (ERD/ERS) are used by various researchers to carry out BCI tasks [1-4]. In EEG-based BCIs, motor imagery (MI) patterns are commonly used for extracting the neural information. Its operation is based on a rhythmic power decrease or increase in counter-lateral primary sensorimotor areas during preparation for actual movement or imagination of a movement, which are called event related desynchronization (ERD) and event related synchronization (ERS) respectively [4]. The predominant frequency bands of these patterns are very much subject-dependent and it introduces a high inter-subject variability in MI-based BCIs.

For detecting ERD/ERS effects, the Common Spatial Pattern (CSP) algorithm was proven to be effective in calculating subject-specific discriminative spatial filters [5]. Traditionally, manual tuning or setting a broad band filter are employed for frequency band selection in CSP works [6]. Extensions of CSP algorithms such as Common Sparse Spectral Spatial Pattern (CSSSP) [6], Common Spatio Spectral Pattern (CSSP) [7], Sub Band CSP (SBCSP) [8], Filterbank CSP (FBCSP) [9], and Adaptive FBCSP [10] are available in literature in order to choose the optimal frequency band automatically. An effective method for selecting subject-specific frequency bands in MI based BCI is discussed in this paper.

In this paper, we propose a new method to determine the subject-specific discriminative filters from a coefficient decimation based filterbank, instead of subject-specific band selection using time-frequency fisher ratio map followed by adaptive filter design in AFBCSP [10]. Also the fusion of static and dynamic CSP features employed in the proposed framework improved the classification performances of all subjects. The proposed method is applied to publicly available BCI competition III dataset IVa, which were collected from a two-class MI BCI task with five subjects named 'aa', 'al', 'av', 'aw' and 'ay' who performed right hand and foot imagination. The data for each subject comprises 280 trials of EEG measurements from 118 electrodes, sampled at 100Hz.

The paper is organized as follows: Section II presents the proposed method; Fusion of static and dynamic features is explained in section III; Section IV discusses the results obtained and Section V has our conclusions.

II. PROPOSED METHOD

The proposed filterbank based system, Discriminative FilterBank CSP (DFBCSP), has four stages as illustrated in Fig.1. These stages are filter selection, multi-band filtering , calculation of features using CSP algorithm and feature classification.

A. Filter Selection (FS)

EEG signals recorded by electrodes on sensorimotor cortices give the highest discrimination between MI tasks [4]. For the subject-specific filter selection, the sensorimotor cortex channels are filtered using a Coefficient Decimation Filterbank (CDFB) designed using coefficient decimation (CD) technique. The CD technique is proposed in [11] to implement low complexity reconfigurable Finite Impulse Response (FIR) filters. The basic principle of CD is as follows: If every M^{th} coefficient of a finite impulse response (FIR) filter *h(n)* (called modal filter) is kept unchanged and all other coefficients are replaced by zeros, we get $h'(n)$, that has a multi-band frequency response:

$$h'(n) = h(n).c_M(n) \qquad (1)$$

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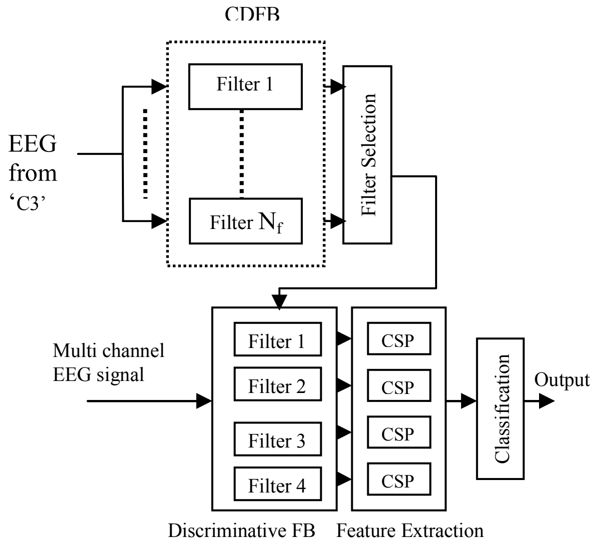


Figure 1. Proposed Discriminative Filterbank based BCI system.

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

The frequency response of $h'(n)$ is scaled by M with respect to that of $h(n)$ and the replicas of the frequency spectrum are introduced at integer multiples of $2\pi/M$. By changing the value of M, different numbers of frequency response replicas located at different centre frequencies can be obtained. In the sequel, we call this CD method as CDM-1. The passbands of the multi-band response obtained using CDM-1 will have identical widths as that of the modal filter. If all the coefficients of the coefficient decimated filter obtained using CDM-1 are grouped together after discarding the in-between zeros, a decimated version of the original frequency response is obtained whose passband width is M times that of the original modal filter. We call this method as *CDM-2*.

If the multi-band frequency responses obtained using CDM-2 are selectively masked using inherently low complex wide transition-band frequency response masking filters, different lowpass, highpass, bandpass, and bandstop filters can be obtained. This can be illustrated using the following example. Let H_0 be the modal filter whose passband and stopband edges are 0.5 Hz and 0.8 Hz as in Fig. 2. Using CDM-1 for M_1=4 and then applying CDM-2 will increase the passband width of H_0 by 4 times as in H_1. Further, if CDM-1 is applied on H_1 for M_2=4, we will get a multi-band response H_2 as in Fig. 2. The desired passband can be extracted from the multi-band filter H_2 using a suitable masking filter. For a fixed M_1, uniform bandwidth filters at different centre frequencies can be obtained by varying M_2. In this work, we chose the values of M_1 and M_2 such that the uniform passband widths of every filter in the filterbank is varied from 2 Hz to 6 Hz and centre frequencies of the passband lie in the range of 5 Hz-45 Hz. Fig. 3 shows the frequency responses of 15 filters in CDFB corresponding to the M_1=4 and M_2 varying from 3 to 10. It can be noted from Fig. 2 that coefficient decimation deteriorates the stopband attenuation. This deficiency can be overcome by an over-designed modal filter (by increasing the filter length) taking into account of the stopband deterioration. As the effective length of coefficient decimated over-designed filter is still considerably less than that of prototype filter in conventional filterbank, the net complexity of the CDFB is still less than the latter.

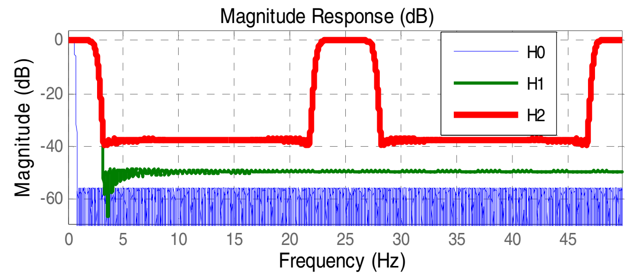


Figure 2. Frequency responses of H_0, H_1 and H_2.

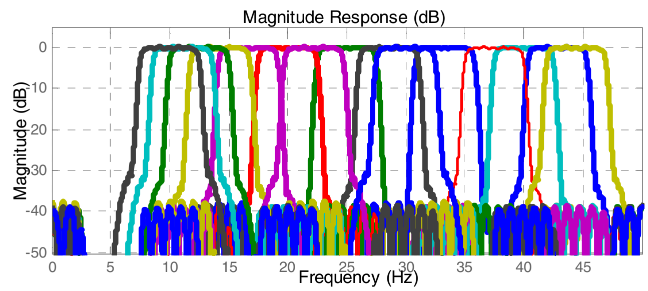


Figure 3. Frequency responses of 15 filters for M_1 =4 and M_2=3 to 10.

The effectiveness of three channel selection possibilities are verified in this work as (i) GC3-a group of 10 channels surrounding 'C3' (ii) C3-raw 'C3' and (iii) LC3-laplacian filtered 'C3' [5]. These signals are passed through the designed CDFB and output power of each subband is measured as an estimate of spectral power over the associated subband for right hand and foot MI patterns using

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

where $P(f_i, t)$ corresponds to the spectral power estimated in i^{th} filter output for the t^{th} trial and T is the number of samples in filtered EEG signal $x^f(n)$. Thus we obtain an N_f x N_t matrix corresponding to spectral power where N_f is the number of filters and N_t is total number of trials. While using multiple channels 'GC3' for filter selection, the average power over the ten channels is estimated to obtain this matrix. 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 for all the filter outputs. Fisher ratio is known as a measure of discriminabilty between two classes of MI patterns. The fisher ratio at each filter output is calculated using equation:

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

$S_W = \sum_{k=1}^{C} \sum_{t=1}^{N_t} (P_t - m_k)^2$ 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), n_k denotes the number of trials for class k. Then four filters corresponding to the highest F_R values are only used for further data processing.

B. Band pass Filtering

An N_f channel filterbank is minimized to a discriminative filterbank of 4 filters, as described in the section *A*. From the experiments, it is found that only four filters are sufficient for good classification performance. Increasing the number of filters did not improve the system performance. The multi-channel raw EEG signals recorded from the scalp are filtered using this discriminative filterbank for further processing.

C. CSP based Feature Extraction and Classification

The goal of the CSP algorithm is to design spatial filters that give a new time series whose variances are optimal for the discrimination of two-classes of EEG measurements. CSP algorithm is based on the simultaneous diagonalization of two covariance matrices [5]. For a single trial EEG **E,** the spatially filtered signal **Z** is given as

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

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 measurement samples per channel and W is the CSP projection matrix. The first and last m rows of Z, i.e. Z_p, $p\in\{1,\ldots,2m\}$ form the feature vector F_p given in (6) as inputs to a classifier [5-10].

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

In this work, the CSP features are extracted from four discriminative filter outputs and therefore each trial is accompanied with 8 features corresponding to m =1 in the CSP algorithm. Then features are classified using Support Vector Machine (SVM) classification algorithm.

III. ENHANCEMENT OF PERFORMANCE BASED ON FUSION OF STATIC AND DYNAMIC FEATURES

The study in [12, 13] reports that features from derivatives of EEG signal can improve the classification performance. Therefore in order to enhance the distinguishability of MI tasks, dynamic features are applied in the proposed DFBCSP using a Delta -transformed EEG signals according to (6)

$$\frac{\partial x(t)}{\partial t} = x^{\Delta}(t) = \frac{\sum_{i=-K}^{K} w_i x(t+i)}{\sum_{i=-K}^{K} w^2{}_i} \tag{6}$$

where $(2K+1)$ is the time-domain window-width (TD_w) for transformation and w_i is corresponding weights applied to each sample in EEG signal *x(t)*.

The performances of static and dynamic features are verified using raw EEG and transformed EEG in the proposed framework named as S_DFBCSP and Dy_DFBCSP respectively. Dynamic feature extraction improved the classification performance of 4 subjects and one subject was performing best with static features. Therefore we did the fusion of features in the proposed frame work as shown in the Fig. 4, Fus_DFBCSP. TD_w varied from 3 to 11 samples in our experiments. The aim of feature fusion was done to utilize the subject-specific optimal model corresponding to the best classification performance of each subject.

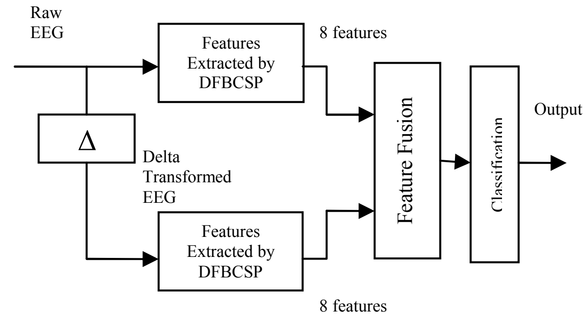


Figure.4. Fusion of static and dynamic features using proposed algorithm.

If F_S and F_D represent static and dynamic features for each subject respectively, the resulting feature F after fusion is a function of α, β and TD_w given in equation (7).

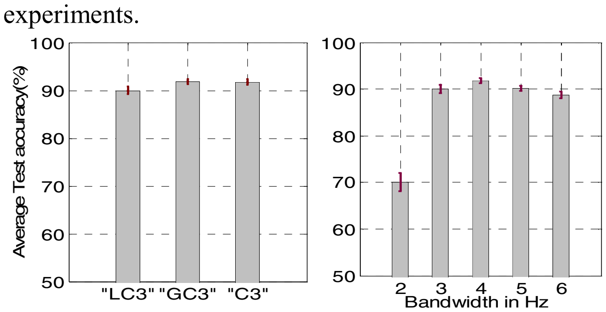
$$F = \begin{bmatrix}\alpha F_S & \beta F_D\end{bmatrix} \tag{7}$$

where the α and β values are subject-specific optimal parameters, can be either 1 or 0, depending on the selection/rejection of static and dynamic features denoted by F_S and F_D respectively. Results of the Fus_DFBCSP framework are discussed in section IV.

IV. RESULTS AND DISCUSSIONS

We test our methods on BCI Competition III dataset IVa. Estimated features after band pass filtering are classified by an SVM classifier. The proposed method is compared with the existing FBCSP [9] and AFBCSP [10] algorithms. FBCSP algorithm deployed 9 fixed filters followed by feature selection and classification and AFBCSP deployed subject-specific frequency bands and same feature selection and classifier as in [9]. The comparison of FBCSP, AFBCSP and Fus_DFBCSP are given in the following section.

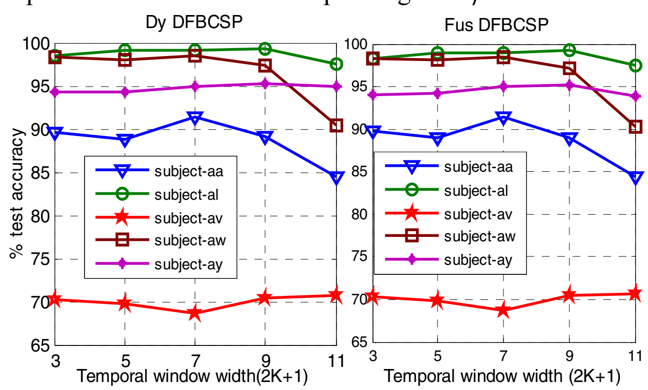
Fig. 5 (a) shows the average test accuracy over 5 subjects for 'C3', 'LC3' and 'GC3' channel selection methods for choosing discriminative filters and Fig. 5(b) displays the average results for various bandwidths 2, 3, 4, 5 and 6Hz for the filterbank, using S_DFBCSP algorithm. It is observed that bandwidth of 4Hz gives maximum accuracy and system performance corresponding to filter selection using raw 'C3' alone is very close to that of multichannel 'GC3' method. So we used 4Hz bandwidth filters and channel "C3" for the discriminative filter selection in the experiments.



5 (a) 5(b)

Figure 5. Test accuracy results of S_DFBCSP using raw EEG signal.

For Dy_DFBCSP, the variations of test accuracy of each subject vs. TD_w are plotted in Fig. 6 (a). It is observed that Dy_DFBCSP improves test accuracy slightly for subjects 'aa' and 'aw' at TD_w =7 and 'al' and 'ay' at TD_w =9 compared to S_DFBCSP. Increasing the temporal window width beyond 9 samples degraded the performance for the 4 subjects. But the performance of the subject 'av' was poor (70.71% for TD_w=9) for all window widths analyzed, compared to S_ DFBCSP (77.79%). Also TD_w increment beyond 11 did not help 'av'. Therefore subject-specific optimization in terms of α, β and TD_w values is done in Fus_DFBCSP framework which can deliver the best results for each subject. Fig. 6 (b) shows the results for fusion framework for α=β=1. But none of the subjects showed improvement for fusion corresponding to α=β=1.



6 (a) 6(b)

Figure 6. Percentage test accuracy of 5 subjects V/s TD_w for 5 subjects.

The performances of S_DFBCSP, Dy_DFBCSP and Fus_DFBCSP are tabulated in Table I. Column II represents the best accuracy obtained for subjects 'aa, 'al', 'av', 'aw' and 'ay for TD_w equals 7, 9, 11, 7 and 9 samples respectively in Dy_DFBCSP. The optimal subject-specific parameters α, β and TD_w are selected for Fus_DFBCSP as given in column IV and the average test accuracy is 92.44 ± 0.54% over 5 subjects.

Table I Classification accuracy (%) for 5 subjects.

subject	S_DFBCSP α =1 β=0	Dy_DFBCSP α =0 β=1	Fusion Parameters, α , β ,TD_w	Fus_DFBCSP
'aa'	90.21 ± 0.56	**91.36 ±0.92**	0, 1, 7	91.36 ± 0.92
'al'	98.68 ± 0.29	**99.29 ± 0.02**	0, 1, 9	99.29 ± 0.02
'av'	**77.79 ± 0.99**	70.75 ± 1.22	1, 0, 0	77.79 ± 0.99
'aw'	97.86±0.376	**98.46 ±0.41**	0, 1, 7	98.46 ±0.41
'ay'	94.21±0.538	**95.29 ± 0.37**	0, 1, 9	95.29 ± 0.37
			Average test Accuracy	**92.44 ± 0.54**

Table II Average test accuracy over 5 subjects

Method	Average Test Accuracy (%)	T-test Results
FBCSP	90.00±0.82	-Baseline-
AFBCSP	90.3±1.35	p = 0.68 (not significant)
Fus_DFBCSP	92.44±0.54	p = 0.0006 (significant)

Therefore subject-specific parameter optimization gives average test accuracy of 92.44 ± 0.54 over 5 subjects in Fus_DFBCSP model and Table.II shows the comparison of proposed method with existing FBCSP and AFBCSP algorithms. Experimental results and statistical analysis of t-test prove that accuracy of proposed method is significantly better than the conventional filterbank methods.

V. Conclusion

We proposed a discriminative filterbank selection method for classification of EEG signal recorded for right hand and foot imagery tasks. The proposed DFBCSP algorithm effectively determines the subject-specific discriminative filters from EEG signal recorded from channel "C3". We then proposed to combine static EEG and dynamic EEG and fuse features derived from both signals. We achieved average cross-validation test accuracy of 92.44%, which is significantly better than previous methods. In this study, we only deployed a simple fusion method. Other fusion methods can be exploited in the future to possibly further improve the performance.

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