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An Adaptive Filter Bank for Motor Imagery based Brain Computer Interface

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Abstract—Brain Computer Interface (BCI) provides an alternative communication and control method for people with severe motor disabilities. Motor imagery patterns are widely used in Electroencephalogram (EEG) based BCIs. These motor imagery activities are associated with variation in alpha and beta band power of EEG signals called Event Related Desynchronization/synchronization (ERD/ERS). The dominant frequency bands are subject-specific and therefore performance of motor imagery based BCIs are sensitive to both temporal filtering and spatial filtering. As the optimum filter is strongly subject-dependent, we propose a method that selects the subject-specific discriminative frequency components using time-frequency plots of Fisher ratio of two-class motor imagery patterns. We also propose a low complexity adaptive Finite Impulse Response (FIR) filter bank system based on coefficient decimation technique which can realize the subject-specific bandpass filters adaptively depending on the information of Fisher ratio map. Features are extracted only from the selected frequency components. The proposed adaptive filter bank based system offers average classification accuracy of about 90%, which is slightly better than the existing fixed filter bank system.

I. Introduction

EEG is widely used in detecting brain activities by recording electric signals from the scalp. Intentions can then be recognized by analyzing the neurological phenomenon from the EEG signals. It gives rise to a new communication and control channel, dubbed brain computer interface (BCI), which does not depend on the brain's normal output pathway of nerves and muscles. BCI can be used as a communication tool for people with severe neuromuscular disabilities, such as amyotrophic lateral sclerosis, brain-stem stroke, spinal code injury, etc., to control external devices such as a computer, wheelchair, neuroprothesis etc. EEG based BCIs use 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), etc [1-4].

Motor imagery is one of the effective methodologies employed in EEG-based BCIs [5]. Preparation for actual movement or imagination of a movement is accompanied by a rhythmic power decrease or increase in counter-lateral primary sensorimotor areas, which are called event related desynchronization (ERD) and event related synchronization (ERS) respectively [6]. The predominant frequency bands are very much subject-dependent, which will be the main concern of this paper.

In order to detect motor imagery intention, the common spatial pattern (CSP) algorithm was found to be effective in calculating subject-specific discriminative spatial filters for detecting ERD/ERS effects. Given two classes in a high dimensional feature space, the CSP algorithm finds directions (spatial filters) that maximize the variance of one class and minimize the variance of the other one simultaneously [8]. Traditionally, the frequency bands at which the CSP works the best were either manually tuned or set to a broad band filter [9]. In order to automatically choose the optimal frequency band, [10] proposed Common Spatio Spectral Pattern or CSSP algorithm. CSSP tried to optimize the frequency filters for each channel together with spatial-filters. Further, to make it more flexible in frequency filtering, Common Sparse Spectral Spatial Pattern (CSSSP) algorithm [9] was proposed to optimize an arbitrary finite impulse response (FIR) filter within the CSP analysis. Sub-band CSP (SBCSP) [11] was then proposed to filter the multi-channel EEG signals using Chebyshev type 2 infinite impulse response (IIR) filter bank. The score values computed from the SBCSP features were used to determine the classification capabilities of each frequency bands. The recent study in [12], proposed Filter Bank Common Spatial Pattern (FBCSP), which deployed a fixed filter bank of 9 equal bandwidth Chebyshev type 2 IIR filters followed by feature selection and classification algorithms.

In this paper, we further the work at [12] to propose a method to determine the subject-specific discriminative frequency bands adaptively based on time-frequency map of Fisher ratio between two-class multi channel EEG signals, and implement the filters with reconfigurable bandpass Finite Impulse Response (FIR) filters based on coefficient decimation technique. The proposed method is applied to publicly available BCI competition III dataset IVa, which were collected from a two-class motor imagery BCI task with five subjects named 'aa', 'al', 'av', 'aw' and 'ay' who performed right hand and left foot imagination. The data for each subject comprises 280 trials of EEG measurements from 118 electrodes. The data are sampled at 100Hz.

The paper is organized as follows: section II explains the proposed method, section III discusses the results obtained and section IV has our conclusions.

II. Proposed Method

The proposed adaptive filter bank based system for two-class motor imagery pattern has five stages as illustrated in Figure 1. These stages comprise the calculation of time-frequency Fisher ratio map, multi-band filtering using

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reconfigurable FIR filters, calculation of features using CSP algorithm, feature selection, and classification.

In order to find out the predominant frequency bands from EEG, Fisher ratios are calculated across time-frequency domain. After selecting the informative frequency components using Fisher ratio, we employ the desired bandpass filters realized using coefficient decimation based reconfigurable filter bank. Thus the multichannel EEG signals go through variable bandwidth bandpass filtering and spatial filtering. Each filter of EEG is followed by a number of spatial filters to yield CSP features that are specific to each frequency range of that bandpass filter. The next stage is feature selection which finds out the most discriminative pairs of CSP features from all the CSP features out of all the filter bands. The final stage is a Support Vector Machine (SVM) classifier to recognize the class of the motor imagery.

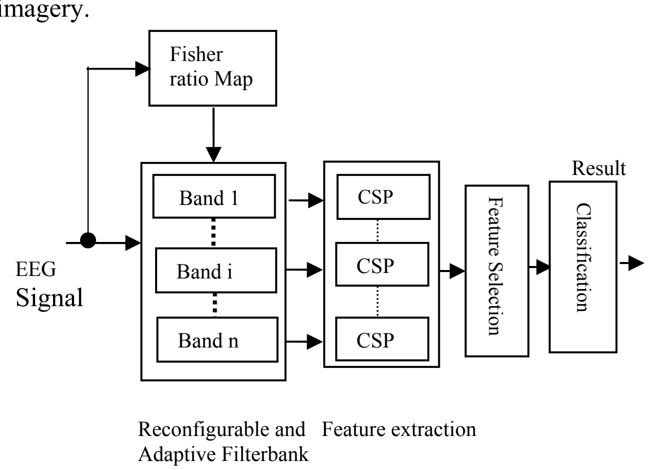

Figure 1. Proposed Adaptive Filter Bank Based BCI System.

A. Time-frequency Fisher Ratio Map

Given each trial of EEG, we first calculate the power spectral density (PSD) in shifting time windows (width=400ms, overlap=200ms) using Short Term Fourier Transform (STFT) on each channel and average the PSD over the channels from sensorimotor cortices. So each trial is associated with a discrete time-frequency density map $I(f,t)$. Fisher ratio, F_r, is then calculated to measure the discriminative power of each time-frequency point across trials and classes.

$$F_r(f,t) = \frac{S_B}{S_W} \quad (1)$$

$$S_W = \sum_{k=1}^{C} \sum_{I=w_k} (I - m_k)^2$$

$$S_B = \sum_{k=1}^{C} n_k (m - m_k)^2$$

where 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, S_W is the within class variance and S_B is between class variance. The time-frequency Fisher ratio is used to indicate informative frequency components, where high values represent more discriminative time-frequency components.

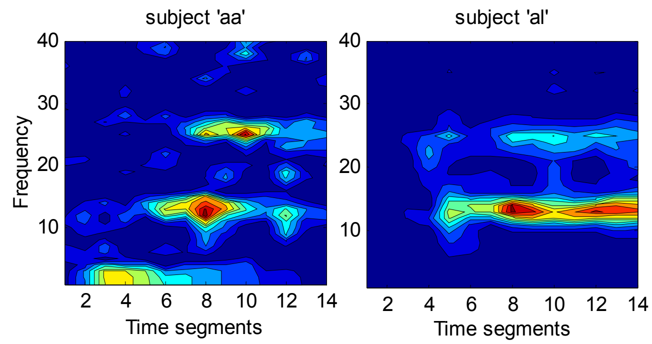

Figure 2. Time-frequency Fisher ratio plots for subjects named 'aa' and 'al' in BCI competition III dataset IV a.

After getting the time-frequency Fisher ratio map, we will search for the predominant frequency band by a shifting window along the frequency axis. To start, a window slides from 4Hz to 40Hz along the frequency axis of Fisher ratio map, and we calculate the total value of Fisher ratio within this window over the whole time course as

$$\alpha(f_i, BW_j) = \sum_{f=f_i-BW_j/2}^{f=f_i+BW_j/2} \sum_{t=1}^{T} F_r^{\,2}(f,t) \quad (2)$$

Where f_i is the centre frequency of the window, BW_j is the bandwidth, and T is the duration of the trials. BW_j varies from 3-9Hz, Then, for each band width, we select the band with centre frequency f_j corresponding to

$$f_j = \arg\max_i \{\alpha(f_i, BW_j)\}$$

This way, we select a frequency band for each bandwidth, together with their maximum total values α. We then need to decide from all the frequency bands which one will be used for filter design. To do so, we first find out the maximum α among all bandwidths for a particular frequency band, $\alpha_{max}(f,BW)$, and then calculate the relative change of each α towards the maximum value as

$$\eta = \frac{\alpha(f_j, BW_j) - \alpha_{\max}(f, BW)}{\alpha_{\max}(f, BW)} \times 100\% \quad (3)$$

We discard all those bands with η below certain value (eg, 5% in our case). Finally we find the band with largest bandwidth, which is denoted as Band-1. In the same way, we can find out other frequency bands with the constraints that only some overlap is allowed between any two bands (eg, 1 Hz in our case). Band searching continues until a maximum number of bands (eg, 9 in our case), or with the *α* value lower than certain percentage of that of Band 1 (eg, 12 % in our case). The shift of the window along frequency axis can vary from 0.1 to 1Hz.

B. Adaptive Filter Bank system using Coefficient Decimation (CD) Approach

From the bandpass selected above, we can then design FIR filters. Here, we employ a reconfigurable filter bank based on Coefficient Decimation (CD) approach [7] for adaptive frequency filtering. Linear phase FIR filters are widely employed in many filtering applications because of the advantages such as guaranteed stability and low coefficient sensitivity. But the main problem of FIR filters lies in its high implementation complexity due to the requirement of higher order compared to its IIR counterpart. A new approach to implement computationally efficient reconfigurable FIR filters was presented in [7]. If the coefficients of an FIR filter (termed modal filter) are decimated by M, i.e., if every M^{th} coefficient of the filter is kept unchanged and remaining coefficients are changed to zeros, a multi-band frequency response will be obtained.

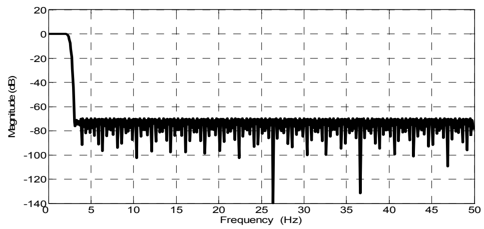

Figure 3(a). Frequency response of modal filter.

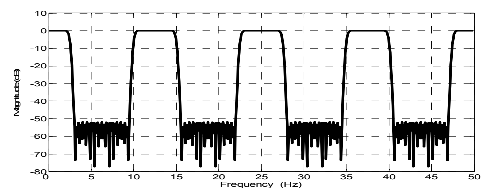

Figure 3(b). Frequency response of modal filter with M=8.

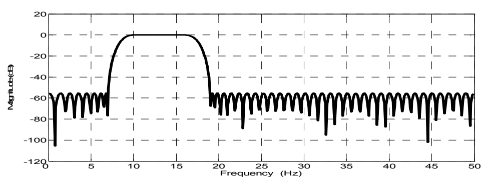

Figure 3(c). Frequency response of masking filter.

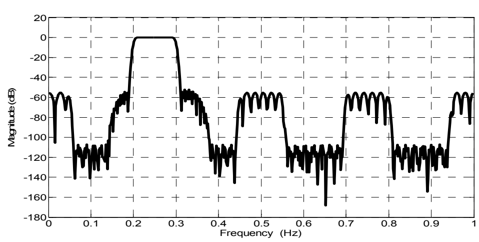

Figure 3(d). Frequency response of Band-1 filter for subject 'aa'.

Let $h(n)$ be the original set of filter coefficients. If we replace all the coefficients other than every M^{th} by zeros

$$h^{'}(n) = h(n)c_M(n) \tag{4}$$

where $c_M(n) = 1$ for n=mM, m=0,1, 2 etc.

= 0 otherwise.

The Fourier transform of modified coefficients $h'(n)$ is given by [7]:

$$H(e^{jw}) = \frac{1}{M}\sum_{k=0}^{M-1} H(e^{j\left(w-\frac{2\pi k}{M}\right)}) \tag{5}$$

It can be noted from equation (5) that, the frequency response is scaled by M and replicas of frequency spectrum are introduced at integer multiples of $2\pi/M$, where the centre frequencies are at $2\pi k/M$ and k is an integer ranging from 0 to M-1.

If these multi-band frequency responses are selectively masked using inherently low complex wide transition-band masking filters, different low pass, high pass, bandpass, and band stop filters can be obtained. We employ the CD-based reconfigurable filter bank in proposed feature extraction method on account of its absolute control over the location of centre frequencies of pass bands.

For example, for one of the subjects 'aa' in the dataset we used, the informative frequency bands obtained from time-frequency Fisher ratio plot are 11-15Hz (Band-1), 6-12Hz (Band-2) and 23-28Hz (Band-3). Below are the steps in the design of Band-1 (11-15 Hz) for this subject.

Step 1: The passband and stopband specifications of modal filter are chosen as 2 Hz and 3 Hz respectively. Then modal filter response is shown in Fig. 3 (a).

Step 2: If the modal filter is decimated by M=8, the frequency response as shown in Fig. 3(b) is obtained. The centre frequency of Band-1 is 13 Hz for subject 'aa' and this can be obtained by choosing k=1 as given in (5).

Step 3: A masking filter with frequency response as shown in Fig. 3(c) is used to isolate Band-1 from the decimated frequency response of modal filter.

The final frequency response of Band-1 after masking is shown in Fig. 3(d). Note that the stopband attenuation of the final filter is slightly inferior to that of the modal filter, but this deterioration is taken into consideration by overdesigning the modal filter such that the final filter's stop band response will satisfy the desired response. Thus for each subject, the passband edges of 'n' bandpass filters are obtained from the Fisher ratio plots and then the modal filter coefficients are adaptively adjusted (k and M values are varied) according to the centre frequency and bandwidth requirements using coefficient decimation technique.

C. *Common Spatial Patterns (CSP)*

After spectral filtering using the adaptive filter bank in B, EEG signal from each filter band will be applied with a CSP transformation to obtain features for classification. The goal of the CSP algorithm is to design spatial filters 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 [8]. The spatially filtered signal Z of a single trial EEG E is given as

$$Z = WE \tag{6}$$

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 rows of W are the stationary spatial filters and the columns of W^{-1} are the common spatial patterns.

The spatial filtered signal Z given in (4) maximizes the differences in the variance of the two-classes of EEG measurements. However, the variances of only a small number m of the spatial filtered signal are generally used as features for classification [8]. The m first and last rows of Z, i.e. Z_p, $p \in \{1,..., 2m\}$ form the feature vector F_p given in (7) as inputs to a classifier.

$$F_p = \log\left[\left(\mathrm{var}(Z_p)\right) / \left(\sum_{i=1}^{2m} \mathrm{var}(Z_i)\right)\right] \quad (7)$$

D. Feature Selection and classification Algorithms

As the features from the filter and CSP are highly dimensional, feature selection is deployed to reduce the number of features for classification. It helps to improve the robustness of the classifier. Among the wrapper and filter based approaches of feature selection algorithms available in literature, we used Mutual Information (MI)-based best individual feature selection in filter approach as in [12] i.e. from an initial set F with d features, find the subset $S \subset F$ with 'FS' pairs of features that maximizes Mutual Information. This algorithm requires a user defined parameter to select the number of best features ('FS'). Then the selected features are given to the Support Vector Machine (SVM) classification algorithm which is a linear discriminant that maximizes the separation between two-classes based on the assumption that it improves the classifier's generalization capability.

III. Results and Discussions

We test our method on BCI Competition III dataset IVa, which comprises of 280 trials of EEG measurements from 118 electrodes for each subject. The subject-specific frequency bands are determined using time-frequency Fisher ratio for that subjects and the EEG is processed with the proposed reconfigurable filter bank based on the frequency bands selected. We take 2.5s to 4.5s (after the visual cue) of the filtered EEG data to calculate CSP features. Then the feature selection algorithm selects the best CSP features (based on mutual information criterion) and sends them to an SVM classifier. We also compared our method with FBCSP [12]. FBCSP algorithm deployed 9 fixed filters. The proposed AFBCSP method deployed subject-specific frequency bands, and we use the same feature selection and classifier as in [12]. Average accuracy results of five subjects with 10x10 fold cross-validations for FBCSP and AFBCSP are shown in Table I. Experimental results and statistical analysis of t-test, show that accuracy of proposed method is similar to FBCSP, however, AFBCSP usually ends up with much less number effective bands (usually 3) and the adaptive filter gives rise the potential for on-line adaptation. Also the filters are designed by less complex CD technique. Thus AFBCSP yields less computational complexity in terms of filtering and subsequent CSP formation than FBCSP which employed 9 bandpass filters.

Table I. Average Test accuracy over five subjects

Value of feature selection parameter('FS')	Proposed AFB CSP (%)	FBCSP (%)[12]
1	89.1±1.43	88.48±0.71
2	90.0±1.36	89.25±0.90
3	90.2±1.32	89.88±0.73
4	90.3±1.35	90.0±0.82

IV. Conclusion

We proposed an adaptive filtering method (AFBCSP) for multiple filter band CSP classification of motor imagery EEG signal. AFBCSP determines the predominant frequency bands for each subject using the information from time-frequency Fisher ratio map. The filter design is based on coefficient decimation technique, which was originally suggested for implementing reconfigurable filters at a lower complexity where the centre frequency and bandwidth of the filters can be easily varied. Experimental results show that AFBCSP gave good results comparable to the state of the art which uses more number of filters. The adaptive nature of the AFB system which is obtained at a lower complexity is promising. Furthermore, it can be potentially used for online adaptation. The Hardware implementation of the proposed approach is possible at a lower cost which will be looked upon in near future.

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