# Decimation Filter with Common Spatial Pattern and Fishers Discriminant Analysis for Motor Imagery Classification

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*Abstract*—**Brain Computer Interface (BCI) system converts thoughts into commands for driving external device with Electroencephalography (EEG). This paper presents the use of decimation filters for filtering the EEG signal. Common Spatial Pattern (CSP) technique is used to transform the filtered signal to a new time series in order to have optimal variance for the discrimination of different tasks. Fishers Discriminant Analysis (FDA) is applied to the CSP features and the FDA scores are fed to a Support Vector Machine (SVM) classifier. The method is evaluated on BCI Competition III Dataset IVa and compared with other related state-of-the-art approaches. The results show that our method outperforms all other approaches in terms of average classification error rate. Compared to best performing method that uses only CSP features, the results obtained in this research offer on average a reduction of 1.07% in the classification error rate.**

***Keywords—brain computer interface (BCI); common spatial pattern (CSP); electroencephalography (EEG); Fishers discriminant analysis (FDA); motor imagery.***

## I. Introduction

Advances in technology with the main aim of making lives of people much easier have led to an increase in the number of research in the context of Brain Computer Interface (BCI). In this era, BCI or Brian-Machine Interface (BMI) is one of the hot research topics, with a huge attention and application to the biomedical engineering community [1-8]. Measuring the brain activities using EEG is gaining a wide-spread interest offering huge potentials for diagnosis [9] and treatment of mental diseases, brain diseases and abnormalities [10-19].

A BCI system could be helpful in restoring valuable tasks of severely disable people. The first BCI application was established in 1964 [20] by Grey Walter. The application used EEG recordings for controlling a slide projector. With technological advancements, devices having low cost and reduced complexity such as Neurosky Mindwave [21] and Emotiv EPOC/EPOC+ headset [22] have been developed, which are used in BCI research and applications.

EEG, magnetoencephalogram (MEG), and functional magnetic response imaging are used for recording the brain activities for noninvasive BCI systems. However, mostly EEG is used in engineering applications [23, 24] due to its high temporal resolution and the simplicity of the device. The electrodes are placed along the scalp of the brain to record the changes in the electrical signal. The acquired EEG signal is contaminated by other noises such as Electrocardiogram (ECG), Electrooculogram (EOG) and Electromyogram (EMG). Techniques such as adaptive filters and blind source separation (BSS) [25, 26] have been proposed to remove EOG and ECG artifacts while the use of independent component analysis (ICA) [27-29] has been widely explored for muscular artifact removal. Generally, data acquisition, preprocessing, feature extraction and classification are the processes involved in a BCI system. Preprocessing is mostly performed for artifact removal. For feature extraction, a number of feature extraction methods have been proposed [30-33], common spatial pattern (CSP) [34-39] being widely used technique. A number of classifiers commonly used are support vector machine (SVM) [32, 40-46], k-Nearest neighbors (k-NN) [47-49], and Random Forest [50, 51].

The CSP technique was first utilized for the detection of abnormalities using EEG [52]. Later, CSP was applied to discriminate movement-related patterns [53], and afterwards used for motor imagery classifications. In CSP, spatial filters are designed such that the new time series data obtained after transforming the original EEG signal using the spatial filters gives maximum discrimination between the different motor imagery tasks. In [34], a sub-band common spatial pattern (SBCSP) for BCI is presented. The signal is firstly decomposed into multiple bands using 24 Gabor filters, each having a bandwidth of 4 Hz. In the second stage, SVM Recursive Band Elimination (RBE) is employed for selecting the top ten bands with most discriminating features. In this method, the sub-band scores are concatenated. The authors also

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employed Meta-Classifier (MC) as a second method for fusion the of the sub-band features scores in order to avoid the iterative scheme involved in the training phase of RBE. In this case, SVM is again used for classification.

A filter bank CSP (FBCSP) algorithm for BCI application is presented in [35], comprising of four advanced stages of EEG signal processing. In the first stage, the EEG signal is filtered into multiple bands using zero-phase Chebyshev type II bandpass filters having a bandwidth of 4 Hz in the frequency range of 4-40 Hz. Spatial filtering using CSP technique is then performed on each of the bands yielding CSP features that are specific to the frequency bands of the bandpass filter. In the third stage, feature selection algorithm is employed to select the discriminative CSP features. Several feature selection algorithms such as mutual information based best individual feature (MIBIF), mutual information based naïve Bayesian Parzen window (MINBPW), mutual information based feature selection (MIFS) method adopted by Battiti [54], the new fuzzy-rough set-based feature selection (FRFS2) and mutual information based rough set reduction (MIRSR) have also been evaluated. The final stage employs classification which involves evaluating several classifiers such as SVM, k-NN, etc. The maximum average classification accuracy obtained using BCI Competition III Dataset IVa was 90.3% [35]. Another discriminative common spatial pattern (DFBCSP) method is presented in [38]. The authors in their paper showed that using the bands that have most discriminating features improves the classification accuracy. They also showed that different subjects have different frequency bands with discriminating features. Signal from channel C3 or C4 is used to obtain best four filter banks with discriminating features. The fisher ratio (FR) is calculated from the estimate of the spectral power of each sub-band. The four filter banks having the highest FR values contain better discriminating power. Thus the EEG signal is filtered using these four filter banks. CSP is then performed to obtain the sub-band CSP features. The sub-band features are then fed to the SVM classifier for classification. Coefficient decimation technique [55] has been employed for the filters.

Lu et al. [36] proposed a regularized CSP (R-CSP) with aggregation for EEG classification in a small-sample set in order to address the problem that the EEG classification accuracy deteriorates when the numbers of training samples is small. In this method, the covariance matrix estimation is regularized by two parameters ($\beta$, $\gamma$) in order to lower the estimation variance and reducing the estimation bias at the same time. Then the problem of finding the best regularization parameters arises. To tackle this problem, the authors proposed R-CSP with aggregation (R-CSP-A). In the regularization process, EEG samples from other subjects (other than the subject of interest) are utilized. The R-CSP-A approach showed improvement in the classification rate compared to the conventional CSP algorithm.

In this paper, we propose a decimation filter bank CSP with Fishers Discriminant Analysis (FDA) for EEG classification of motor imagery tasks. SBCSP and FBCSP employ four stages having multiple filter banks resulting in sub-bands. In SBCSP band selection if employed while in FBCSP feature selection is performed. This paper proposes the use of a single band for all the subjects (eliminating the use of band selection), reducing the computational complexity as R-CSP-A. Thereafter, FDA is applied to the CSP features to get discriminant features useful for classification. In this paper we call this method CD-CSP-FDA.

The rest of the paper is organized as follows. Section II presents the decimation filter, CSP and FDA algorithm for the application of EEG signal classification. Section III describes the dataset used and provides the experimental results of the proposed system. Finally, Section IV draws the conclusion and gives insight of some future works.

## II. CD-CSP-FDA METHOD

The proposed coefficient decimation (CD) filter bank CSP with FDA system is shown in Fig. 1. It filters the EEG signal (after common average referencing is performed) using a single bandpass decimation filter with bandpass frequency in the range of 8-28 Hz with a passband ripple of 5 dB and stop-band ripple of 70 dB. The filtered signal is then transformed to new time series using the conventional CSP algorithm. The CSP features are then extracted from this new time series data. FDA is then applied to the CSP features to obtain the FDA scores, which are then fed to the SVM classifier in order to determine the class of EEG signal. Each of the EEG processing phases in the proposed algorithm is carried out using MATLAB and is explained in detail in the following sub-sections.

### A. Filtering using Decimation Filter

The decimation technique offers the ability to obtain bands with desired center frequencies. In our proposed method, decimation technique is employed for filtering the EEG motor imagery signal. In the decimation technique, every $M^{th}$ coefficient of the finite impulse response (FIR) filter *h(n)* (called modal filter) is kept unchanged while all other coefficients are replaced by zeros. The frequency response of the resulting decimation filter *h'(n)* is a multiband response, whose size is reduced by a factor of *M* with respect to that of the original response *h(n)*. The multiband response of the passband and that of the modal filter will have identical widths. Alternatively, decimation filter can also be obtained by only using the nonzero coefficients and discarding zeros placed in between. It must also be noted that there is an upper limit ($Mf_{st}$<0.5) to the value of *M* after which aliasing error could occur, where $f_{st}$ is the normalized stopband edge of the modal filter with respect to the sampling frequency [55].

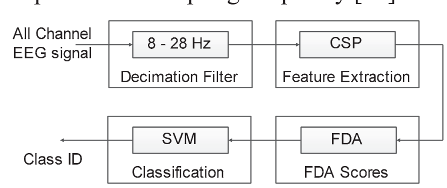


Fig. 1. Block diagram of proposed method.

### B. Common Spatial Pattern (CSP)

After bandpass filtering using decimation technique, spatial filters are designed using the CSP algorithm. The main aim of

CSP is to transform the data onto a new time series having optimal variance for discrimination between the two classes of EEG signal [53]. In the CSP algorithm, the normalized covariance matrix of each class ($\overline{C}_c \in R^{N_{ch} \times N_{ch}}$) is given by (1), where $E_{(c,n)} \in R^{N_{ch} \times T}$ (single trial EEG data from $N_{ch}$ number of channels with each channel having $T$ number of samples) is the $n^{th}$ trial of class $c$ and $N_c$ being the total number of trials in the respective class with $c = \{1,2\}$.

$$\overline{C}_c = \frac{1}{N_c} \sum_{n=1}^{N_c} \frac{E_{(c,n)} E_{(c,n)}^T}{trace(E_{(c,n)} E_{(c,n)}^T)} \tag{1}$$

Thus the spatial covariance is given by (2), where $U$ is the eigenvector matrix and $D$ is the diagonal matrix with its diagonal element arranged in descending order.

$$C = \overline{C}_1 + \overline{C}_2 = UDU^T \tag{2}$$

The whitening transformation matrix $P \in R^{N_{ch} \times N_{ch}}$ is thus obtained using (3) and the average covariance matrices are transformed using (4).

$$P = D^{-1/2} U^T \tag{3}$$

$$S_1 = P\overline{C}_1 P^T \text{ and } S_2 = P\overline{C}_2 P^T \tag{4}$$

Simultaneous diagonalization of $S_1$ and $S_2$ is then performed in (5).

$$S_1 = U_s \Sigma_1 U_s^T \text{ and } S_2 = U_s (I - \Sigma_1) U_s^T \tag{5}$$

Thus the CSP projection matrix $W_{csp} \in R^{N_{ch} \times N_{ch}}$ is obtained using (6).

$$W_{csp} = U_s^T P \tag{6}$$

The filtered EEG signal is thus transformed using (7), with $W_{csp}^*$ made up of first and last $m$ columns of $W_{csp}$, where $Z_{(c,n)} \in R^{2m \times T}$.

$$Z_{(c,n)} = W_{csp}^{*T} E_{(c,n)} \tag{7}$$

The CSP feature vector having a dimension of $2m$ is then constructed using (8), where $Z_{(c,n)}^p$ denotes the $p^{th}$ row of $Z_{(c,n)}$, and $y_{(c,n)}^p$ denotes the $p^{th}$ component of $y_{(c,n)} \in R^{2m \times 1}$.

$$y_{(c,n)}^p = \log[\text{var}(Z_{(c,n)}^p)], \quad p = 1,...,2m \tag{8}$$

Finding all $y_{(c,n)}$ results in a matrix $Y \in R^{2m \times (N_1 + N_2)}$. Since there are 2 classes, $Y$ can be divided into 2 sets; $X_1$ for class 1 and $X_2$ for class 2, where $X_1 \in R^{2m \times N_1}$ and $X_2 \in R^{2m \times N_2}$.

### C. Fishers Discriminant Analysis (FDA)

Linear discriminant analysis (LDA), also known as FDA has been successfully used in many applications [56-61] and thus has been employed in this research. In FDA, the cost function in (9) is maximized, where $S_B$ and $S_W$ are the between-class and within-class scatter matrices respectively.

$$J(v) = \frac{v^T S_B v}{v^T S_W v} \tag{9}$$

$S_B \in R^{2m \times 2m}$ and $S_W \in R^{2m \times 2m}$ for two class problem are given by (10) and (11), where $X_c \in R^{2m \times N_c}$ is the sample set of class $c$, and $\mu_c$ (for $c$ =1,2) is the centroid of class $c$.

$$S_B = (\mu_1 - \mu_2)(\mu_1 - \mu_2)^T \tag{10}$$

$$S_W = \sum_{c=1}^{2} \sum_{x \in X_c} (x - \mu_c)(x - \mu_c)^T \tag{11}$$

The solution to the problem in (9) is obtained using (12) and the CSP features are then transformed using the FDA transformation matrix (as given in (13)) in order to obtain the matrix $u \in R^{1 \times (N_1 + N_2)}$ containing the FDA scores of the entire dataset. Alternatively, eigenvalue decomposition could have also been used to solve the problem. The FDA scores obtained are fed to the SVM classifier.

$$v_{FDA} = \arg\max_v \left( \frac{v^T S_B v}{v^T S_W v} \right) = S_W^{-1}(\mu_1 - \mu_2) \tag{12}$$

$$u = v_{FDA}^T Y \tag{13}$$

## III. Results and Discussions

The publicly available BCI Competition III Dataset IVa [62] have been used for evaluating the proposed method. The dataset consists of EEG signals for right hand and left foot motor imagery tasks. It contains EEG signals from 118 channels at positions of the extended international 10/20 system [63], which are recorded from five subject's referred to as 'aa', 'al', 'av', 'aw' and 'ay'. The signal was sampled at 100 Hz. The training and test data provided have been merged together due to the small number of data for training. Therefore, the dataset contains 280 trials of EEG measurement for each subject, having equal number of trials for each class. According to [64], data between 0.5 seconds and 2.5 seconds (i.e. 200 time points) after the visual cue has been used, as used by other related works. For the filter bank, the decimation technique is used with the value of $M$ taken as one in order to prevent aliasing. For extracting CSP features in this research work, the value of $m$ is taken as 3, as recommended in [65]. The temporal filters have been manually tuned.

The classification performance of the proposed method is performed using 10 and 5-fold stratified cross validation (method used to evaluate other existing algorithms). However, for statistical stability we performed 10x10-fold and 10x5-fold stratified cross validation. In the 10-fold validation procedure the dataset is randomly divided into ten equally divided partitions, each partition having equal number of each class data. One of the partitions is then used for testing while the other nine partitions are used for training the model. Similarly, one by one each partition is used once as testing while others are used for training the model. Then the whole process is repeated ten times and all the results are averaged and used for performance evaluation.

TABLE I. CROSS VALIDATION CLASSIFICATION ERROR RATE OF DIFFERENT METHODS

| No. | Method | Filter | *k* | *m* | Folds | Percentage (%) Classification Error Rate | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | ***Subject aa*** | ***Subject al*** | ***Subject av*** | ***Subject aw*** | ***Subject ay*** | ***Average*** |
| 1 | CSP [66] | - | 1 | 1 | 5 | 24.29 ± 12.7 | 6.43 ± 2.99 | 36.79 ± 5.14 | 2.14 ± 1.96 | 7.14 ± 3.79 | 15.36 |
| 2 | SBCSP-RBE [34] | Gabor | 24 | 1 | 10 | 9.20 ± 4.5 | 2.20 ± 3.4 | 31.0 ± 7.3 | 4.20 ± 3.3 | 5.00 ± 3.4 | 10.30 |
| 3 | FBCSP [38] | Chebyshev Type II | 9 | 2 | 10 | 6.93 ± 0.58 | 0.97 ± 0.24 | 31.0 ± 1.42 | 4.90 ± 0.89 | 6.18 ± 0.97 | 9.99 |
| 4 | CSP (simple weighting technique) [66] | - | 1 | 1 | 5 | 23.57 ± 11.32 | 6.07 ± 5.14 | 34.64 ± 2.71 | 4.29 ± 2.04 | 6.79 ± 4.07 | 15.07 |
| 5 | CSP (Sparsity-aware) [66] | - | 1 | 1 | 5 | 19.64 ± 12.81 | 4.64 ± 4.48 | 28.93 ± 7.08 | 2.14 ± 1.96 | 6.43 ± 2.99 | 12.36 |
| 6 | CD-CSP-FDA (this paper) | Coefficient Decimation | 1 | 3 | 5 | 12.59 ± 1.96 | 1.87 ± 0.53 | 24.89 ± 0.47 | 4.03 ± 1.12 | 5.32 ± 0.90 | 9.74 |
| | | | | | 10 | 12.01 ± 0.60 | 1.73 ± 0.59 | 23.67 ± 0.47 | 3.18 ± 1.11 | 4.03 ± 0.39 | 8.92 |

In Table I, the classification error rates of all five subjects together with the average classification error rate of the proposed CD-CSP-FDA method is shown along with other methods that have used the same dataset for performance evaluation. All the methods in Table 1 use CSP features only and SVM classifier except the CSP, CSP (simple weighting technique) and sparsity-aware methods that used LDA as the classifier. *k* is the number of different frequency bands that have been used. From the results in Table I, it can be noted that the proposed method performed well and the results are very promising as it produced the least classification error rate (8.92%) in terms of average classification error rate compared to the state-of-the-art methods. Considering the individual subjects result, subjects 'ay' and 'av' produced the optimal results using the proposed method. For subjects 'al', 'aw' and 'ay' the individual subject results are not optimal using the proposed method, however the results are still promising and better than few state of the art methods. The proposed method performed best for subject 'al' having a classification error rate of 1.73 percent while the worst performance was noted for subject 'av' having a classification error rate of 23.67 percent.

Moreover, the proposed method is computationally less expensive compared to state-of-the-art methods such as SBCSP and FBCSP. In SBCSP and FBCSP, multiple bands are used with either band selection or feature selection algorithm. Although the use of multiple bands showed improvement in the performance of the system, it should also be noted that it also leads to an increase in the computational complexity of the system. In our proposed method, a single band is used and the feature vector has a dimension of one, which greatly reduces the computational cost of the system. The proposed method, takes the advantage of the discriminating power of the CSP projection matrix by using the value of $m$ as three ($m$=3) compared to one ($m$=1) used by SBCSP and two ($m$=2) used FBCSP.

In this work, the proposed method is not compared with methods that uses other types of features such as that in [67] where dynamic system features are used with CSP features. The method obtained a result of 7.80% classification error rate, which is better than the proposed method. However, as mentioned earlier this research work only focused on CSP method with CSP features only. Therefore, to further improve the classification error rate other types of features and methods to remove low quality signals can be studied and incorporated in the proposed system that may further improve the system.

## IV. CONCLUSION

In this paper, FDA is proposed with CD-CSP for motor imagery tasks. It employs single bandpass filter designed using decimation technique to replace the use of multiple filters as in SBCSP and FBSCP. Thus, eliminating the need for band selection. FDA is used to generate FDA score for classification. The proposed method has enhanced the classification error rate of the BCI competition III Dataset IVa. Compared to the best performing method FBCSP, the CD+CSP+FDA method offers a reduction of 1.07% in the classification error rate for 10-fold cross validation.

The preliminary results obtained are quite promising and future work includes testing the method on other datasets with larger population. It is recommended that other frequency bands with narrow bandwidths in the lower frequency band be studied so that the value of $M$ can be increased resulting in the reduction of the computational complexity of the system. Also the effect of using different values of $M$ and other different types of features can also be studied.

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