A Study on the Impact of Spectral Variability in Brain-Computer Interface

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***Abstract*— The performance of a Brain-Computer Interface (BCI) depends on reliable feature extraction and accurate classification. Motor imagery has been successfully used in BCI for communication and control. During motor imagery, for EEG based BCI, it was known that the discriminative frequency bands are subject-specific. Moreover, such discriminative frequency bands for each subject might vary from time to time. In this paper, we investigate the variability of discriminative spectral ranges and its impact on classification accuracy. It is found that for each subject, his discriminative frequency bands changes significantly from session to session, but keeps almost stable within a session. We then propose a method to adaptively update the discriminative frequency bands using Time-Frequency fisher ratio. From the experimental analysis, it is found that we can reduce the average error rate by 11.50% compared to the case where fixed discriminative frequency bands obtained from calibration session are used.**

I. Introduction

The ultimate goal of Brain-Computer Interface (BCI) technology is to provide an alternative communication and control channel for people with severe motor disabilities. The use of motor imagery (MI) patterns in Electroencephalogram (EEG) in BCIs is a feasible method to translate the user's intent to the commands to control artificial devices. The performance and reliability of all BCI applications rely mostly on the accuracy of classification. Therefore extraction and representation of MI related EEG features play a vital role in the BCI system [1]. It has been observed that the MI evokes neural activation in brain, especially on primary motor cortex. MI tasks are associated with short lasting Event related De/synchronization (ERD\ERS) patterns [2]. Also the precise timing and frequency of ERD/ERS vary among subjects. The non-stationary nature of the ERD\ERS patterns causes high inter-subject and intra-subject variability in MI based BCIs. The Common Spatial Pattern (CSP) algorithm is an effective tool for detecting these ERD\ERS effects and to calculate subject-specific discriminative spatial filters [3]. Traditionally, manual tuning or setting a broad band filter are employed for frequency band selection in CSP-based works. Extensions of CSP algorithms such as Common Sparse Spectral Spatial Pattern (CSSSP), Common Spatio-Spectral Pattern (CSSP), Filter bank CSP (FBCSP), Adaptive FBCSP and Discriminative Filter bank CSP are available in literature in order to choose the optimal frequency band automatically [4-7]. In [6], we have proposed a subject-specific discriminative frequency band selection using the Time-Frequency (T-F) fisher ratio during right hand and foot MI tasks. After estimating the discriminative bands from the calibration data, required bandpass filters are designed and CSP features are extracted from the filtered EEG signal during testing. In both [6] and [7], the frequency bands estimated from the calibration data itself are used for the test data also. But the frequency bands containing discriminative information may vary with time. Therefore, in this paper, we investigate the variability of discriminative spectral changes and its impact classification accuracy of MI tasks. The proposed method in the current work keeps track of the frequency domain variations in EEG signal. Also its classification accuracy is compared with BCI system where fixed discriminative frequency bands obtained from calibration are used. The analysis is done using publicly available BCI competition IV dataset IIb, which were collected from a two-class MI BCI task for 9 subjects who performed right hand and left hand MI. The data for each subject comprises 5 sessions, with EEG measurements from 3 electrodes C3, Cz and C4, and sampled at 250Hz. The paper is organized as follows: Section II presents the methodology used; the inter-session spectral variability is explained in section III; Section IV discusses the results obtained and Section V has our conclusions.

II. Methodology Used

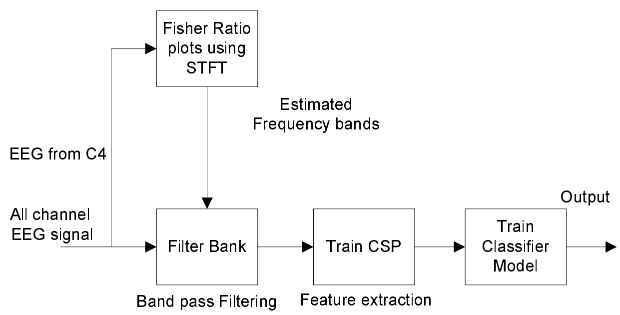


Fig. 1. Discriminative Spectral features based BCI system during Calibration.

The filter bank based BCI system, with subject-specific discriminative features, has four stages [6]. These stages are frequency band selection, multi-band filtering, calculation of features using CSP algorithm and feature classification. After selecting the informative frequency components using T-F

Fisher ratio plot, we employ the desired bandpass filters realization using a coefficient-decimation based reconfigurable filter bank [8]. Each bandpass filter of EEG is followed by a number of spatial filters to yield CSP features that are specific to each frequency range of that band pass filter. Among the 5 sessions available in the discussed dataset, session-1 of each subject is used as the training data to develop the training model and the model is applied on the other 4 sessions. Thus, session-1 acts as calibration session and other 4 sessions as test sessions. The training model parameters include the discriminative frequency bands from calibration session, CSP projection matrix for spatial filtering and Classifier model. The framework shown in Fig. 1 is used during training.

A. Frequency Band Estimation

EEG signals recorded by electrodes on sensorimotor cortices give the highest discrimination between MI tasks [2]. For the subject-specific frequency band selection from the training data, we adopt the same method proposed by us in [6]. The BCI competition IV dataset IIb analyzed here is having the right hand and left hand MI tasks. Therefore EEG channel C4 alone is sufficient to estimate the discriminative frequency bands [7]. In order to find out the predominant frequency bands, fisher ratios are calculated across T-F domain from channel C4. Fisher ratio is known as a measure of discriminabilty between two classes of MI tasks. Given a single trial EEG, the power spectral density in shifting time windows using Short-Time Fourier Transform (STFT) is calculated. Thus each trial is associated with a discrete T-F density map $I(f,t)$. Then fisher ratio F_R is calculated to measure the discriminative power of each time frequency point across trials and classes.

$$F_R(f,t) = \frac{S_B}{S_W} \tag{1}$$

$S_W = \sum_{k=1}^{C}\sum_{n=1}^{n_K}(I_n - m_k)^2$ and $S_B = \sum_{k=1}^{C} n_k(m-m_k)^2$ are the within-class variance and between-class variance respectively, m_k is the average for class k, $(k = 1,2), m$ is the average over k classes and n_k denotes the number of trials for class k. Then the dominant frequency bands are automatically located by a band selection algorithm depending on the fisher ratio plot [6]. Fig. 2 shows the T-F fisher ratio plot of Subject-1 in session-3.

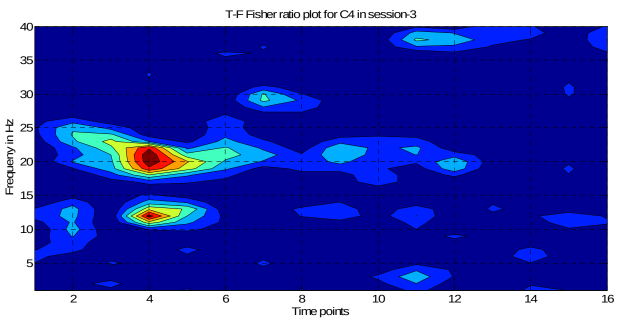


Fig. 2. The T-F fisher ratio plot in session-3 of subject-1. Frequency bands 19-23 Hz and 11-14 Hz are selected by the algorithm for further processing.

B. Band pass Filtering

After estimating the subject-specific discriminative frequency bands from T-F fisher ratio plots, as described in the section A, the desired bandpass filters are realized. For this, reconfigurable Finite Impulse Response (FIR) filters are designed based on the coefficient-decimation (CD) approach proposed in [8]. It is a computationally efficient approach to realize FIR filters that have flexible frequency responses. The basic philosophy of CD is as follows. 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. If these multi-band frequency responses are selectively masked using inherently low complex wide transition-band masking filters, different low pass, high pass, band pass, and band stop filters can be obtained. This technique has absolute control over the locations of center frequencies and passband widths. Therefore depending on the frequency information from T-F plot, desired bandpass filters in the BCI system can be designed from the same set of modal filter coefficients. More details of CD technique can be found in [6, 8]. Thus the required bandpass filters are designed using the CD technique to perform multi-band filtering. From the experiments, it is found that only 2 bands are sufficient for good classification performance. Increasing the number of bands did not improve the system performance in the discussed dataset.

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. For a single trial EEG E, the spatially filtered signal Z is given as

$$Z = WE \tag{2}$$

where 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].

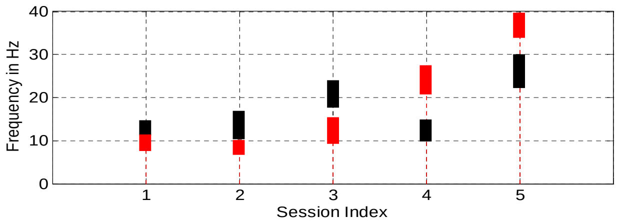
$$F_p = \log\left[(var(Z_p)) \,/ \left(\sum_{i=1}^{2m} var(Z_i)\right)\right] \tag{3}$$

In this work, the CSP features are extracted from two discriminative filter outputs and therefore each trial is accompanied with 4 features corresponding to $m = 1$ in the CSP algorithm. Then features are classified using Naïve Bayesian Classifier [5].

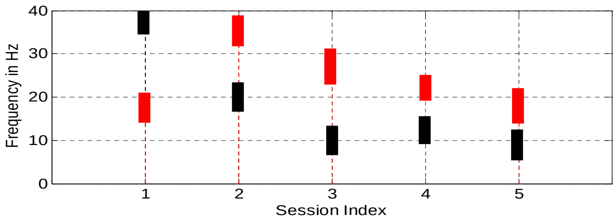
III. Intersession Variability of Frequency Bands

Due to the non-stationary nature of ERD\ERS patterns, the subject-specific discriminative bands may vary with time.

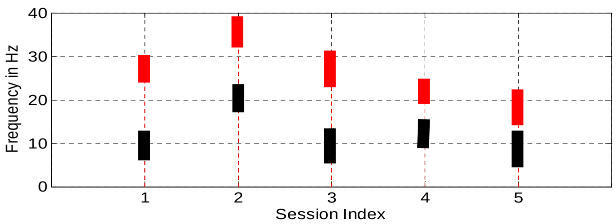
Therefore the discriminative bands selected from calibration session may not be useful for processing other sessions. In order to investigate the variability of discriminative frequency bands during MI, the discriminative bands for various sessions are analyzed separately. In the analysis, it is found that the discriminative frequency information vary between sessions for the same subject. We did 10-fold Cross-Validation separately for the 5 sessions in all subjects and noted the most voted 2 frequency bands among all folds in each session. Again the 10-fold Cross-Validation procedure is repeated processing all folds in these 2 selected frequency bands in the respective sessions for all subjects. Features from these two selected discriminative bands gave comparatively higher classification accuracies in most of the sessions in all subjects. Figures 3(a)-3(c) shows the selected discriminative bands in 5 sessions for Subjects 1, 2 and 3. Fig. 3 shows the significant inter-session variation of discriminative frequency bands. But the degree of discriminative band variation is found to be subject-specific. It is also noted that the variation in same session does not appear as strong as between session variation of frequency bands, i.e. the inter-session variability seems more prominent than intra-session variability.



(a) Subject-1



(b) Subject-2



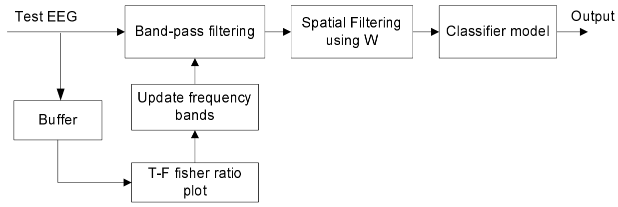
(c) Subject-3

Fig. 3. Variation of discriminative frequency bands in 5 sessions.

From the above analysis, it is observed that that there exists a high inter-session variability of discriminative frequency bands in all the subjects analyzed. Therefore processing of new EEG samples in the frequency bands obtained during the training from session-1, might not correctly classify the tasks. The impact of this spectral variability in classification accuracies of MI tasks is investigated in this work. To accommodate this variability, the BCI system should keep track of variations in frequency domain. As the discriminative frequency bands vary from session to session for all subjects, a new session should incorporate its discriminative bands for improving its classification performance.

For analysis, we present the classification results of the BCI system using static and updated discriminative frequency bands. In Static Spectral Feature (SSF) method, the discriminative frequency bands estimated from calibration session itself is used for test session also, i.e. the spectral variability is not updated in the system when new EEG samples are received as shown in Fig. 4(a). But in Updated Spectral Feature method (USF) given in Fig. 4(b), the system keeps track of variations in discriminative spectral information. After a few trials of MI tasks in the new session, the discriminative bands are updated. The first set of test EEG data is processed in the calibration model frequency bands. Then after every N_1 trials in the test session EEG, discriminative frequency bands are updated using the T-F fisher ratio plot of that N_1 EEG samples. Thus the most recent discriminative frequency information is utilized for the following signals. The buffer shown in Fig. 4(b) is used to keep the EEG signals for frequency band updating. A buffer of 40 trials $(N_1 = 40)$ found to be good enough to obtain discriminative the T-F plot and update the frequency bands.

(a) Employing Static Spectral Features (SSF).



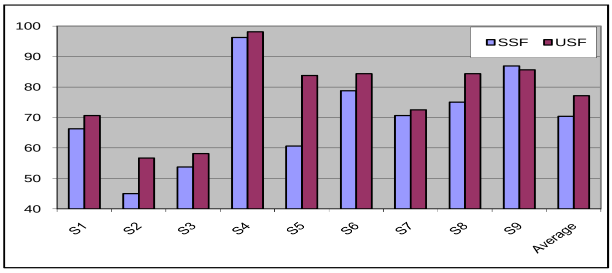
(b) Employing Updated Spectral Features (USF).

Fig. 4. Test framework.

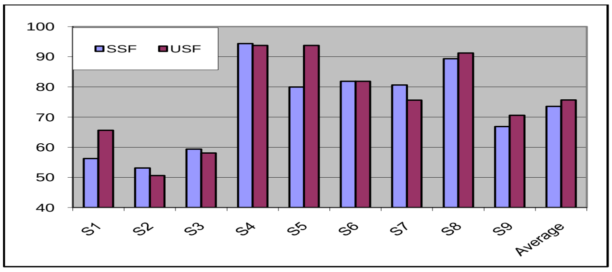
In SSF method, the same training model parameters are used for all sessions and USF method uses the updated frequency bands in test sessions. But train classifier model and CSP projection matrix are kept fixed during testing also, assuming that the discriminative features fall in the same feature space and weights of different channels (CSP projection matrix W) are constant. It means no updating of classifier model or spatial filter W is done in both SSF and USF methods during testing. Only frequency bands and filters are updated in USF method.

IV. RESULTS AND DISCUSSIONS

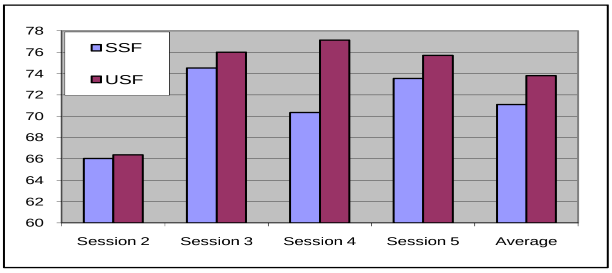
We test our methods on BCI Competition IV dataset IIb. It consists of EEG data from 9 subjects recorded in 5 sessions. Estimated features after band pass filtering are classified by a Naïve Bayesian Classifier [5]. We present the results using both SSF and USF methods. Figures 5(a) and 5(b) show the



(a) In session-4



(b) In session-5



(c) In sessions 2, 3 4 and 5

Fig. 5. Comparison of classification accuracies using Static and Updated Spectral features.

classification accuracies in sessions 4 and 5 respectively for the 9 subjects (S_1 to S_9) in dataset. USF method performs better than SSF in most of the subjects. On average, USF method outperforms SSF as shown in Fig. 5(c), by error rate reductions of 1.01%, 6.21%, 29.90% and 8.84% in sessions 2, 3, 4 and 5 respectively.

For both SSF and USF methods, three calibration model parameters are developed including the discriminative bands, CSP projection Matrix (W or spatial filter) and classifier model during calibration done on session-1. By applying same classifier hyper plane and CSP matrix throughout the testing sessions, we assume that the feature space and spatial filters respectively are similar always. But frequency bands need to be updated in USF. In CSP based feature extraction, the variances of CSP projected EEG signals (spatially filtered EEG signals) constitute the features. In the USF, the features are extracted from the discriminative frequency bands which posses relatively higher fisher ratio values. The fisher ratio is to maximize the inter-class variance and minimize the within-class variance. Since the energy in selected bands gives good discrimination, the application of the same CSP projection matrix might give almost similar results. So we assume that the discriminative bands can be informative even though the spatial filter and classifier hyper plane are not updated.

The proposed Updated Spectral Features method updates the discriminative frequency bands from the new EEG samples and keeps track of informative frequency bands. Thus the most recent information is used for further processing of EEG signals. From the accuracy results, it is observed that the classification accuracies improve in most of the subjects by updating the discriminative frequency components. More effective performance can be achieved by better online adaptation techniques [9]. However the results show that discriminative bands play a significant role even though weights of channels and classifier model are kept fixed all throughout the analysis.

V. Conclusion

The discriminative frequency band variations between various sessions for EEG signal recorded during motor imagery tasks and its impact in classification accuracy are investigated using the proposed filter bank based BCI system. The proposed algorithm effectively determines subject-specific discriminative frequency bands using Time-Frequency fisher ratio values. Also the system keeps track of frequency domain variations in the discriminative features. The processing of test sessions using the classifier model and spatial filter developed from calibration session give promising results, even though the frequency bands and filtering are updated. It gives a new direction for further research. Also online adaptation techniques will be exploited in the future to further improve the performance.

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