Combining CCA and CFP for Enhancing the Performance in the Hybrid BCI System

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***Abstract*— Hybrid Brain Computer Interface (BCI) is gaining attention as it can provide better performance or increase the number of user commands to control an external device. Hybrid BCI system using Motor imagery (MI) and Steady-state visually evoked potential (SSVEP) is one such system. Maintaining the performance during channel reduction is important in practical applications. In this paper we propose a combined feature extraction method using Canonical Correlation Analysis (CCA) and Common Frequency Pattern (CFP) method, where the features obtained from these methods were combined for classification. We used LDC and PARZEN for estimating the classification accuracy for the proposed method and individual method. Highest accuracy of 96.1 % is obtained for combined feature method (CCA+CFP). Whereas, the accuracy is 89.6% with CCA and 91.6% with CFP method. A significance test has shown that the performance of the proposed method is significantly different from both the individual methods ($p < 0.05$).**

I. Introduction

With Brain Computer Interface (BCI) as a medium of communication, user can control or interact with an external device. Motor Imagery (MI) [1], Steady state visually evoked potential (SSVEP) [2], P300 [3] etc., are some of the patterns commonly used in many electroencephalography (EEG) based BCI system. With an increased demand for the number of user commands or higher classification accuracy, Hybrid BCI systems gained attention [4]. In our study we focus on Hybrid BCI system using MI and SSVEP which has been under study over the past few years with wide range of applications [5,6,7]. In general, MI patterns can be extracted from central region using C3 and C4 channels especially for left and right hand motor imagery as seen in [8]. Similarly, SSVEP based BCI systems use O1 and O2 channels over occipital region. Therefore, the past hybrid BCI systems have been using a group of channels over central and occipital regions in order to extract MI and SSVEP features. Recently, [9] implemented a few channel hybrid BCI system that use only C3, Cz and C4 channels and has shown that besides MI, SSVEP information can also be extracted from these channels. This system used Common Frequency Pattern (CFP) method and has shown that the performance of Hybrid BCI is significantly better compared to either MI or SSVEP based BCI system alone.

Maintaining the accuracy of systems during channel reduction is an important factor in real world applications. Over the years, many techniques have been developed for SSVEP feature extraction [10, 11, 12]. Canonical Correlation Analysis (CCA) has been widely used as it can provide better classification accuracy for SSVEP based BCI systems [11, 12]. However, it is important to note that CFP can extract features from both MI and SSVEP information [9, 10], and CCA can extract feature from SSVEP information only. Simultaneous operation of two BCI modalities (here MI and SSVEP) can increase classification accuracy or reduce BCI illiteracy for users [5]. If a user can perform simultaneous MI and SSVEP, then the system's accuracy can reach maximum, but in the case of BCI illiteracy where the accuracy drops, a single feature extraction method like CFP alone for feature extraction is not sufficient to maintain the classification accuracy.

Therefore, in this paper we propose a combined CCA and CFP method for feature extraction in a two channel (C3, C4) hybrid BCI system using MI and SSVEP to enhance the classification accuracy of the system. It is expected that if any of the user is not capable of performing either MI or SSVEP, this combination of feature method can improve the classification accuracy of BCI system. Linear Discriminant (LDC) and Parzen density (PARZENDC) classifiers were used to estimate the classification accuracy. The performance of our proposed method (CCA+CFP) is compared with the individual methods (CCA or CFP).

A more detailed explanation is given in the results and discussion section. Results show that the proposed method outperformed with both the classifiers. Highest classification accuracy of 96.1% is obtained with combined feature method using LDC. But, with CCA the accuracy is 89.6% and with CFP it is 91.6%. Also, Wilcoxon's matched-pairs signed-ranks test has shown that the combined method differs significantly from the individual method.

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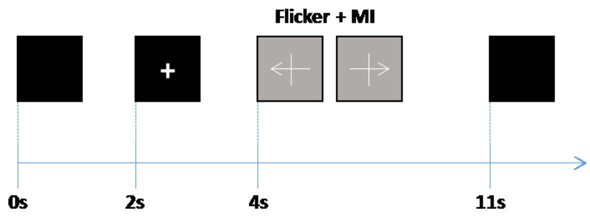

Fig. 1. Example EEG experiment procedure for hybrid task

II. MATERIALS AND METHODS

A. Participants

Eight right handed subjects, 6 male and 2 female, aged between 18 and 29 years (mean age 23±2.6 years) participated.

All the subjects have normal or corrected-to-normal vision and have no history of neurological or physiological or psychiatric disorders. None of them has any prior experience in EEG based BCI experiments.

B. BCI Experiment paradigm

LCD monitor (21 inch, 60 Hz refresh rate, 1920x1080 screen resolution) was used to present flickering stimulus. Two stimuli, (15Hz flicker with right arrow or 20Hz flicker with left arrow) were presented randomly on the screen. As shown in figure 1, the experimental procedure is divided into three steps:

- A blank screen for 2 seconds.
- Fixation step for 2 seconds, during which, the subject will gaze at the cross sign presented at the center of the screen.
- Then a 7 seconds long stimulus is presented on the screen. During left arrow stimulus (with 20Hz flicker), user has to perform left hand imagery movement while simultaneously observing the flicker. Similarly during right arrow stimulus (with 15Hz flicker), user has to perform right hand imagery while observing the flicker.

With each trial consisting of aforementioned steps, 45 trials per stimulus were recorded for each subject.

C. Data acquisition and processing

32 electrodes (Contact Precision Instruments amplifiers, Neuroscan Acquire software) were used for EEG recording. The electrodes were placed according to the International 10/20 system (see Fig. 2). The impedance of all the channels was kept below 5kΩ. The sampling rate of data recording was 500Hz. Only C3 and C4's channel data was considered for further steps.

EEG signal acquired from channels was processed as shown on Figure 3A. It consists of the following steps:

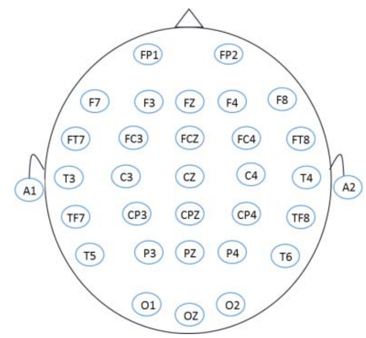

Fig. 2. 32 channel 10-20 internal system. This study uses A1, A2 channel for reference.

- A band pass filter of 1~50 Hz was applied to remove 60 Hz power line noise and other high frequency noise.
- Noise/Artifact removal to avoid discrepancies between pattern determinations.
- A two second fixation was used to record baseline for normalization.
- Epochs were extracted for event related EEG dynamics from continuous data.

D. Common Frequency Pattern

Common Frequency Pattern (CFP) algorithm is similar to Common spatial pattern (CSP), where CSP focuses on spatial filter optimization and CFP focuses on spectral filter such that variances obtained are optimal for discriminating two population datasets (or classes) [13]. CFP takes power spectral density (PSD) as input, which is calculated by performing Fast Fourier transform (FFT) on extracted epoch (see Fig. 3B) to transfer time-domain data into frequency-domain data. We use FFT with 1 second step (500 data points) and overlapping by 0.5 seconds (250 data points) to estimate PSD.

Average covariance of each trial's frequency domain data (E) of dimension NxH (where N is the number of channels and H is number of frequency) is calculated as

$$C = \frac{E'E}{N} \tag{1}$$

The covariance for each group is averaged over trials and summed to calculate the composite covariance as follows

$$C_c = C_l + C_r \tag{2}$$

C_c can be factored as, $C_c = U_c \lambda_c U_c'$, where U_c is eigenvector and λ_c represents diagonal matrix of eigenvalues that are assumed to be sorted in descending order. To equalize the variances in U_c, a whitening transformation is applied such that all the eigenvalues of PC_cP' equal to one.

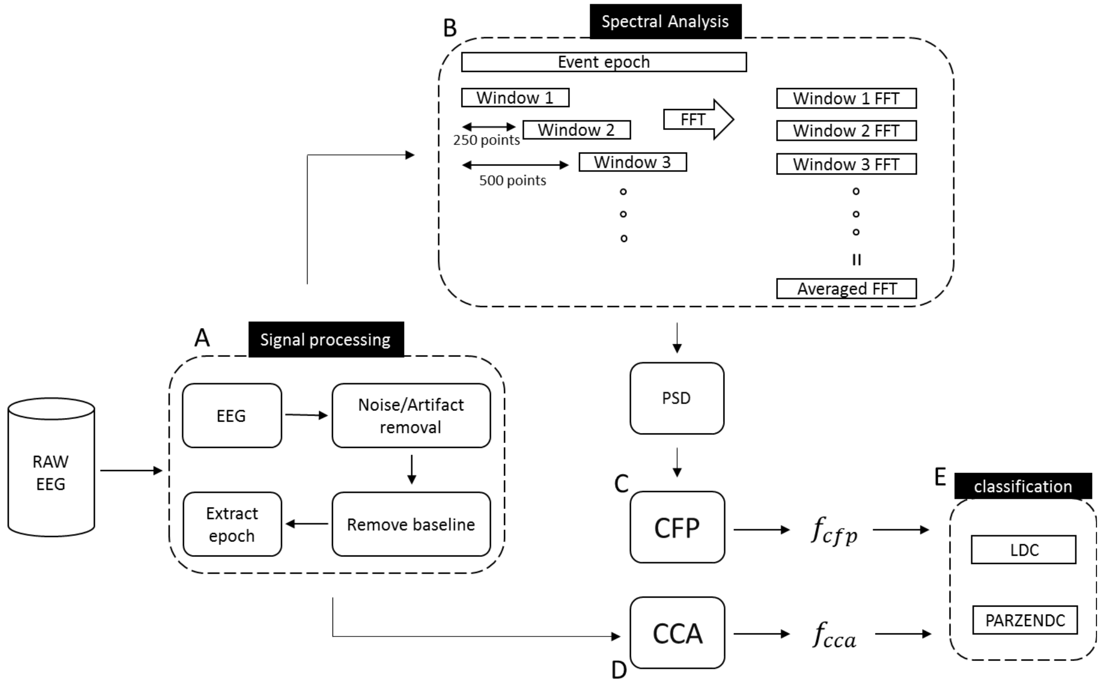

Fig. 3. A framework for EEG analysis in five parts A) Signal Pre-processing, B) Fast Fourier Tranform (FFT), C) Feature extraction using CFP, D) Feature extraction using CCA, E) classification using LDC and PARZENDC.

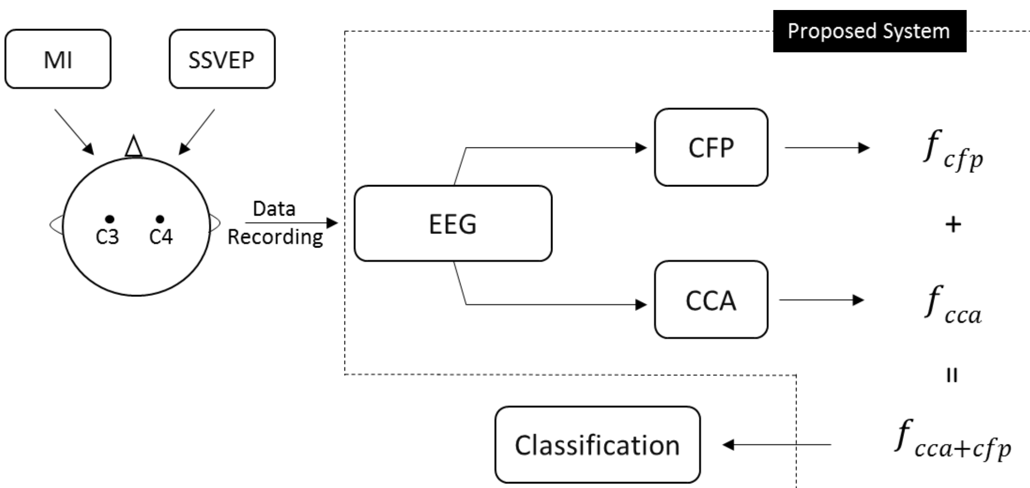

Fig. 4. Framework of the proposed hybrid BCI system for combined feature method.

$$P = \sqrt{\lambda_c^{-1} U_c^{'}} \tag{3}$$

$\overline{C}_l$ and $\overline{C}_r$ are transformed to S_l and S_r so that they share common eigenvectors as

$$S_l = P\overline{C}_l P' , S_r = P\overline{C}_r P' \tag{4}$$

$$S_l = B\lambda_l B' , S_r = B\lambda_r B' , \lambda_l + \lambda_r = I \tag{5}$$

where I is the identity matrix. As sum of λ_l and λ_r is equal to one. The eigenvector with largest eigenvalue for S_l will have smallest eigenvalue for S_r and vice versa. The trial E is mapped with the projection matrix $W = P' B$ as

$$Z = WE \quad (6)$$

W represents a set of filters. Filter W_1 (first filter) provides maximum variance for one class and last filter provides maximum variance for other class. The feature vector f_{cfp} is calculated as

$$f_{cfp} = \frac{diag(\text{cov}(Z_p^{'}))}{N} \quad (7)$$

The signals $Z_p^{'}$ (p = 1, 2, … 2m) selecting the first m and last m filters that maximizes the difference of covariance between two classes are associated with largest eigenvalue λ_l and λ_r .

The feature vector f_{cfp} , obtained with CFP is sent to classification stage to estimate accuracy using two common classifiers (see Fig. 3C).

E. Canonical Correlation Analysis

Canonical correlation analysis (CCA), a multivariable statistical method that measures the underlying correlation between two datasets was first proposed by [14].

CCA maximizes the correlation between two linear combinations by solving the following criterion:

$$\rho = \max_{W,V} \frac{E[xy]}{\sqrt{E[x^2]E[y^2]}} = \frac{W^T XV^T Y}{\sqrt{W^T XX^T WV^T YY^T V}} \quad (8)$$

Where ρ denotes the maximum correlation efficient. X and Y are two sets of random variables with W and V as linear transforms, such that:

$$x = W^T X \text{ and } y = V^T Y \quad (9)$$

Here, $X(t)$ can be considered as multichannel EEG time series and $Y(t)$ as a reference signal constructed in sine and cosine form for each stimuli frequency (f_m = 15Hz or 20Hz) separately as in (10)

$$Y_m = \begin{pmatrix} \sin(2\pi 1 f_m) \\ \cos(2\pi 1 f_m) \\ \sin(2\pi 2 f_m) \\ \cos(2\pi 2 f_m) \\ . \\ . \\ . \\ \sin(2\pi h f_m) \\ \cos(2\pi h f_m) \end{pmatrix} \quad (10)$$

Where m indicates the number of classes and h, number of harmonics.

In this study a feature vector based on CCA is constructed as follows:

$$f_{cca} = [\rho_{15} \quad \rho_{20}] \quad (11)$$

The feature vector f_{cca} , obtained with CCA is sent to classification stage to estimate accuracy with two classifiers (see Fig. 3D). Classification results and statistical analysis for this method and CFP is discussed in section 3.

F. Proposed method

As discussed in section 1, in this study we propose a combined feature method as shown in Fig. 4, and the feature $f_{cca+cfp}$ is constructed from (7) and (11) as follows

$$f_{cca+cfp} = [f_{cca} \quad f_{cfp}] \quad (12)$$

With (12), the new feature set's dimensionality is the sum of the dimensions of feature set (7) and (11).

III. Results

A. Performance

Table 1 shows the average classification accuracy obtained from all the subjects with different feature extraction methods viz. CCA, CFP and CCA+CFP.

Linear discriminant (LDC) and Parzen density (PARZENDC) classifiers were used to estimate the accuracy using 5 –fold cross validation. Highest accuracy of 96.1±3.7% is obtained with LDC under combined CCA+CFP method.

B. Statistical analysis

Before estimating the statistical significance, Kolmogorov-Smirnov test was used to check if the data is distributed normally. This test indicated the normality distribution of data is not fulfilled. Therefore, Wilcoxon's matched-pairs signed-ranks test was performed to find if there exists any statistically significant difference (using p-value) between datasets obtained from different feature extraction methods.

From this test, it is observed that there is significant difference in the performance between CCA+CFP and CFP method (p = 0.015 (with LDC) & 0.078 (with PARZENDC)). Also, CCA+CFP and CCA method has shown significant difference (p = 0.015 (with LDC) & 0.023 (with PARZENDC)) in performance. But, there isn't any statistically significant difference between CCA and CFP method (p = 0.9 (with LDC) & 0.945 (with PARZENDC)).

IV. Conclusion and Discussion

From Table 1 and Fig. 5, it is observed that combined feature from CCA and CFP has better classification accuracy than CCA or CFP method alone and has significant difference in performance with both LDC and PARZENDC classifier. The highest classification accuracy of 96.1% is achieved with

LDC classifier for the combined feature method. With CCA alone the accuracy is 89.7% and with CFP it is 91.6%.

TABLE I. AVERAGE CLASSIFICATION ACCURACY (%) OF HYBRID BCI SYSTEM WITH CCA , CFP AND COMBINED (CCA+CFP) METHOD

Classifier	Accuracy (%)		
	CCA	*CFP*	*CCA+CFP*
LDC	89.7±10.4	91.6±5.8	96.1±3.7
PARZENDC	89.5±10.8	90.9±6.3	95.5±4.2

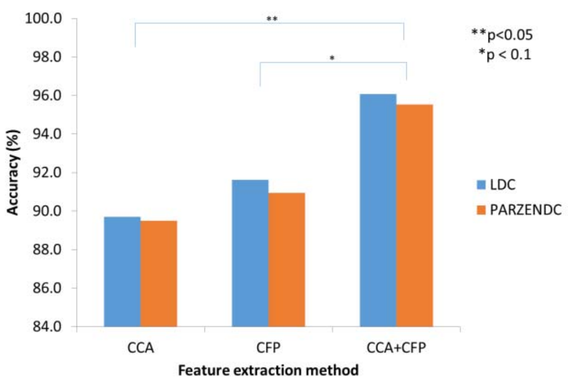

Fig. 5. Performance comparision of combined feature extraciton method and independent methods with LDC, PARZENDC classifeir and Wilcoxon's matched-pairs signed-ranks test.

In general, two or more BCI modalities are composed together to form a hybrid BCI system. The combination can be done either sequentially (to increase the number of user commands or targets) or simultaneously (to enhance the systems' classification accuracy). [7, 15] implemented a sequential hybrid BCI using MI and SSVEP to have multiple command in controlling a wheelchair and humanoid navigation. Authors of these papers implemented CSP for MI task (using C3, C4 channel data) and CCA for SSVEP task (using O1, O2 channels). [5, 9] implemented a simultaneous hybrid BCI system for a two class problem. In our present study we focused on simultaneous hybrid BCI system, where the signal recorded from C3 and C4 channel has both MI and SSVEP information in any time frame. Also, in some other studies, CSP has been widely implemented for MI based BCI systems [7, 16] and CCA for SSVEP based BCI systems.

As mentioned earlier, in simultaneous hybrid BCI system, CFP can extract feature from both SSVEP and MI, whereas CCA extracts feature only from SSVEP. Ideally it is expected for CFP to exhibit better classification accuracy than CCA. But from section 3, with classification results and statistical analysis we found that there is no significant difference in the performance between CCA and CFP methods. This might be due to BCI illiteracy as discussed section 1, i.e., some subjects can perform either MI or SSVEP but not both [17]. For the users who can perform MI and not comfortable with SSVEP (which is clearly evident in Table 1, as a high standard deviation of 10% is obtained in classification results for CCA method), CFP should be able to provide better classification accuracy. In case, if the user cannot perform MI effectively, then CCA method would be better option. Thus, taking into account of channel reduction for few channel hybrid system, BCI illiteracy and the type of hybrid BCI system (sequential or simultaneous), our proposed method can be considered to be best suited to attain good classification accuracy and overcome the drawbacks posed in all these different conditions.

In few channel hybrid BCI system, feature from SSVEP information is extracted from C3 and C4 channel. One potential problem here is that the SSVEP information obtained at these channels might be weak when compared to that obtained from O1 and O2 channels. So, in future work further analysis is required to check if there is any difference in the performance of SSVEP system of C3, C4 and O1, O2 channels. Also, in this study, average accuracy of all the subjects is shown (see table 1). As discussed previously about the presence of individual differences, more subjective analysis is required in this regard and novel methods needs to be explored to develop a universal system that can fit for any user, and achieve maximum performance especially in naturalistic environment, where many external factors that influence the EEG activity [18] play an important role in determining the overall performance of the system.

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