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EEG Filtering based on BSS Algorithm and Its Modification for BCI

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***Abstract*—Biomedical signals have a significant temporal structure. It is obvious to use the blind source separation(BSS) algorithm based on the time lagged covariance matrix for the independent source separation from the multichannel EEG signals. In this paper work, a novel signal preprocessing technique for the enhancement of the rhythmic information related to movement imagination has been presented. The technique is based on the BSS algorithm called as AMUSE algorithm. AMUSE algorithm estimates the separating matrix by an eigenvalue decomposition of a single time lagged covariance matrix of the EEG signals. Human brain has an asymmetrical structure. The asymmetry over the primary motor cortex areas has been incorporated for the modification of the estimated separating matrix. Preprocessing by the modified separating matrix achieve almost 100% classification accuracy between the left and right hand movement imagination. Consequently there is also a significant improvement in Cohen's kappa coefficient.**

***Index Terms*—Asymmetry Ratio, AMUSE Algorithm, Classification Accuracy, Cohen's Kappa Coefficient**

I. INTRODUCTION

Brain activity recorded non-invasive is sufficient to control the external machine, if the advanced method of signal analysis and feature extraction is applied in combination with the machine learning techniques either supervised or unsupervised. Brain computer interface (BCI)/Brain machine interface (BMI) [1] pertains to manipulation or operation of the external machine as per thought of the user and such machine is said to thought controlled machine. Thus there is a direct communication at the level of thought for the action between human and machine via a computer that analyze and interpret incoming physiological signals (electroencephalogram (EEG Signals)), that contain the shadow of a mental activity and many artifacts, and generate control command for controlling the external machine [1]. The concept of thought generation in the human brain is a highly complex process and has not been accessible yet directly as the biological processing and format of the EEG signals are not clearly understood in the brain. However, the levels of thoughts and the types of thoughts have been broadly investigated as change in rhythm, the patterns of the EEG signals capture at the surface of the skull. Although the EEG signals are not a direct access to the levels of thought and thought related actions, it represents shadow of that and hence to some extent thought related patterns can be inferred and used for the controlling action.

For reference, we cite some recent and past work related to movement imagery classification for the BCI system. EEG-based discrimination between imagination of left and right hand movement has been discussed in reference [2] [3]. These papers exploit the event related de-synchronization (ERD) and the event related synchronization (ERS) phenomena for the movement imagery classification. In this study, we compare our results with the recent methods applied on the same dataset, which include a filter bank common spatial pattern (FBCSP) [4] and discriminative frequency band common spatial pattern (DFBCSP) [5]. Still the developed method does not claim 100% thought recognition for the movement imagery. The various leading laboratories of the BCI system have organized the BCI competitions [6] by providing the database of the different mental activity. The database consist of either three channel EEG recordings or greater than three channels. We consider the Graze database (Graze data2b) of the BCI competitions IV [6] [7]. These database have three channels as per 10-20 electrode placement system (C3, Cz and C4) and were recorded for the imagination of the left and right hand movement.

A relevant feature is extracted from the EEG signals for the classification of a mental task. A good feature depends on the preprocessing technique. However 100% thought recognition is still a key problem for either of the statistical classifiers using a single feature vector. In this work, we consider the power spectral density (PSD) [8] of the preprocessed EEG signals as a transform domain feature. To obtain the PSD, we apply parametric AR Burg's spectrum estimation method [8]. The objective of this work is to develop a novel signal preprocessing method which consider the asymmetry property of the human brain over the primary motor cortex area.

EEG signals have a significant temporal structure. The blind source separation method based on a time correlation decorrelates the raw EEG signals and the decorrelated components have no temporal dependencies. The preprocessing of the raw EEG signals by AMUSE algorithm [9] [10] (a second order statistics based BSS algorithm) provides the separating matrix for each of the movement imagery classes. Usually the estimated separating matrix is not orthonormal if it is estimated by a generalized eigenvalue decomposition. As with any eigenvalue problem the order and the scale of the eigenvectors are arbitrary. Hence the recovered signal are arbitrary up to scale and permutation. In the case of AMUSE algorithm, singular value decomposition has been used to factorize a single time lagged covariance matrix. The estimated components are arranged in accordance with the decreasing singular values of a single time lagged covariance matrix of the whitened data. The estimated components have yet the scale ambiguities.

Human brain has an asymmetrical structure. The recorded signals are spatio-temporally correlated. Asymmetry [11] of the human cortex over the primary motor cortex areas and independence condition will have to consider simultaneously. Then it would be possible to estimate the original information source related with different mental activities and consequently there would be an improvement in the classification accuracy. In this study, we are interested in measure the alpha and beta band asymmetry ratio/ multiplier T_f between the estimated separating matrices of the left and right class and its effectiveness on the classification accuracy.

As per classification accuracy we estimate the asymmetry ratio T_f between the separating matrices of the left and right classes in the frequency band 8-30Hz. We also estimate the asymmetry ratio analytically. Since the experimental and analytical values do not have a big difference. So we have chosen experimental value as an asymmetry multiplier. In order to maintain the alpha and beta band (8-30Hz) asymmetry among every trials, we have externally tailored the estimated separating matrix of the left class by an asymmetry multiplier T_f in order to get the almost 100% classification accuracy in every subject.

II. Proposed Method

Biomedical signals have a significant temporal structure. It is obvious to apply the BSS algorithm [9] [10] based on time lagged covariance matrix of the EEG signals for the independent source separation. The entire processes of the BSS algorithm have been categorized into disjoint processing steps such as the whitening, the separating matrix estimation and the independent source estimation. Fig.1 depicts the proposed method. Firstly the EOG signal is corrected by regression coefficient method. The EOG corrected signals are subjected to finite impulse response (FIR) band pass filter having the bandpass characteristics (8-30Hz) to select the rhythmic information. The ensemble averaged EOG corrected EEG signals having the frequency contents (8-30Hz) are processed by the AMUSE algorithm [10] in order to obtain the separating matrix. The estimated separating matrix from the EOG corrected EEG signals do not contain the required asymmetry information over the primary motor cortex areas. It has been found that the ratio between the norm of the separating matrix for the left class and that of the right class should be different. This ratio will provide the condition to select an appropriate asymmetry multiplier. The estimated asymmetry multiplier is used to modify the estimated separating matrix. Filtering based on the updated separating matrix significantly enhanced the classification accuracy over the original separating matrix.

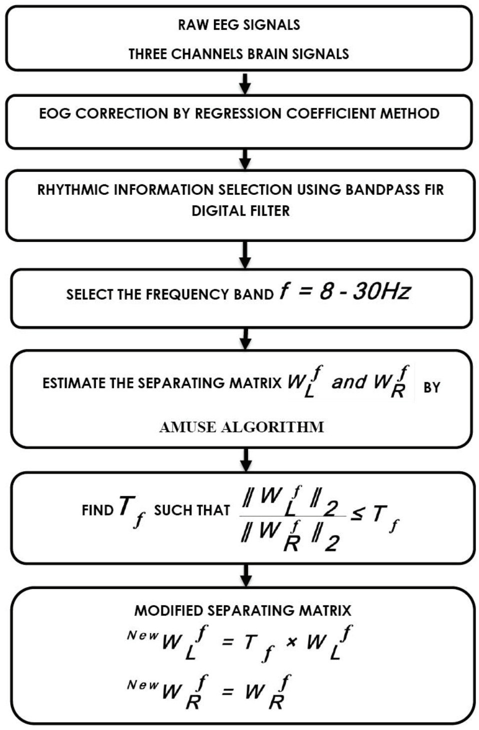

Fig. 1. Proposed method For separating matrix estimation

A. Standard ICA/BSS and its Modification

Blind source separation techniques such as ICA [9] have the ability to extract the relevant information buried within the noise signals and allow the separation of the measured signal into their fundamental underlying independent components or temporally uncorrelated components. In this study, we assume that signal is stationarily time correlated. Before feature extraction it requires decorrelation using the BSS method based on the time structure of the signals. The linear instantaneous mixing model has the following mathematical model

$$X = HS + \omega \tag{1}$$

where

$$X = \begin{bmatrix} x_1(1) & \cdot & \cdot & \cdot & x_1(N) \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_M(1) & \cdot & \cdot & \cdot & x_M(N) \end{bmatrix} \equiv \begin{bmatrix} \boldsymbol{x}_1 \\ \cdot \\ \cdot \\ \cdot \\ \boldsymbol{x}_M \end{bmatrix} \in R^{M \times N}, \tag{2}$$

$\boldsymbol{x}_k = [x_k(1), \cdots, x_k(N)]$ is the observation vector of k^{th} channel. $k = 1, \cdots, M$. Here M stands for the number of channels and N stands for the number of samples. $H_{M \times M}$ is the mixing matrix and the independent source $S \in R^{M \times N}$ in the measurement space. Similarly $\boldsymbol{s}_k = [s_k(1), \cdots, s_k(N)]$ is estimated source vector of k^{th} independent/uncorrelated source just like the observation vector $\boldsymbol{x}_k$. $\omega \in R^{M \times N}$ is the temporally uncorrelated Gaussian noise. The objective of the standard ICA/BSS method is to obtain the separating/unmixing matrix W, which is the inverse of the mixing matrix

H.

We know that the EEG signals contain information in the certain frequency band called as rhythm. In order to retrieve the rhythmic information from the EOG corrected EEG signals $\boldsymbol{x}_k$ in (2) by the regression efficient method, we have applied the bandpass(8-30Hz) FIR filter of order L. The FIR filtered signal $x_k^f(n)$ can be expressed as

$$x_k^f(n) = \sum_{l=1}^{L} b_l x_k(n-l) \in R^{1\times N} \tag{3}$$

where b_l is the FIR filter coefficients, $k = 1, \cdots, M$. The FIR filtered signals of the all channels can be expressed as

$$X^f = [\boldsymbol{x}_1^f, \cdots, \boldsymbol{x}_M^f]^T \in R^{M\times N} \tag{4}$$

AMUSE algorithm [10] uses simple principles that the estimated components should be spatio-temporally decorrelated and be less complex. The components are arranged according to decreasing singular value of a time lagged covariance matrix. AMUSE algorithm can be considered as two step principal component analysis (PCA). In the first step, an eigenvalue decomposition (EVD) of the standard covariance matrix is applied to desired frequency band signals. In the second step, a singular value decomposition (SVD) is applied to a single time lagged covariance matrix of the desired frequency band whitened data (which is obtained in the first step). A short description of the AMUSE algorithm is written below.

StepI. Whitening by EVD.

The covariance matrix $R_{X^fX^f}$ of the desired frequency band is expressed as

$$R_{X^fX^f} = E\left\{X^f(n)\,X^f(n)^T\right\} \equiv V_{X^f}\Lambda_{X^f}V_{X^f}^T \in R^{M\times M} \tag{5}$$

where $X^f(n)$ is desired frequency band signal obtained from the EOG corrected EEG signals X by the the bandpass FIR filter. The symbol E stands for ensemble learning here. Usually in the standard ICA/BSS E stands for the time average. Now the whitening matrix Q^f can be defined as $Q^f = \Lambda_{X^f}^{-1/2}V_{X^f}^T$. V_{X^f} is right eigenvector. The whitened data $Z^f(n) = Q^fX^f(n)$ are given by the linear transformation of the desired frequency band signals in terms of the whitening matrix Q^γ.

StepII.Estimate the separating matrix W^f with SVD.

The time lagged covariance matrix of $Z^f(n)$ is given by

$$R_{zz}^f(n) = E\left\{Z^f(n)\,Z^f(n-1)^T\right\}. \tag{6}$$

The symmetric time lagged covariance matrix is given by

$$R_z^f(n) = \frac{\left[R_{zz}^f(n) + R_{zz}^{f^T}(n)\right]}{2}. \tag{7}$$

Now SVD is applied to time lagged covariance matrix R_z^f and it can be written in factored form $R_z^f = U_z^f\Phi_z^fV_z^{f^T}$ where Φ_z^f is diagonal matrix, whose diagonal value arranged with decreasing singular value and U_z^f,V_z^f are matrices of the eigenvectors. The separating matrix W^f is estimated as $W^f = U_z^{f^T}Q^f$.

Having obtained the separating matrix W^f, suppose W_L^f is the separating matrix for left class and W_R^f is the separating matrix for the right class with respect to the α-band (β-band), which are written as in general form for both classes. Now we define W_i^f, $i \in \{L, R\}$. For better separation between left ($i = L$) and right ($i = R$) class, we find the constraint, which measures the ratio between the euclidean matrix norm $\|.\|_2$ of the left class separating matrix W_L^f and the right class separating matrix W_R^f. We can generalize this ratio and select an asymmetry multiplier T_f which satisfies

$$\frac{\left\|W_L^f\right\|_2}{\left\|W_R^f\right\|_2} \leq T_f. \tag{8}$$

All participants in the BCI competition data set 2b are right handed. It is well known that cerebrum consists of the left and right hemispheres. Each hemisphere of the brain is morphologically different. As per literature survey [11], 90% people are right handed and only 10% are the left handed. Right handed subject is habitual to used the right hand for many kinds of manual tasks. It is also well known that the left hemisphere of the brain controls the right body movement and vice versa. We are considering the primary motor cortex area of the cerebral hemisphere for recording the EEG signals. Basically the primary motor cortex area [**?**] consists of crest of folded cortical tissues called as precentral gyrus and postcentral gyrus. Both gyri have been separated by ac11 grooves that divide gyri from one another is called as central sulcus. By comprehensive survey of the literature [11] [12], it has been found that the left hemisphere central sulcus is larger and deeper compared to that of the right hemisphere for right handed people.

We infer from the above facts that the volumetric areas of the left hemisphere over primary motor cortex will be greater than that of the right hemisphere for right handed people. A large numbers of dipole sources will be active in the left hemisphere compared to the right hemisphere in right hander for right hand movement imagination. That's why the magnitude of the EEG signals in the left hemisphere for the right hand movement will be greater than that of the right hemisphere. ERD and ERS [2] is fundamental phenomenon of motor cortical neurons and there will be a magnitude difference between mean power of left hemisphere (ERD) and the right hemisphere (ERS) for the right hand movement imagination. For the left hand movement imagination, there will be also a magnitude difference between the mean power of the left hemisphere (ERS) and the right hemisphere (ERD) over the primary motor cortex areas in certain frequency bands. The magnitude asymmetry is due to the structural/functional differences between both hemispheres of the cortex for the unilateral movement. This magnitude asymmetry is implicitly related to the estimated separating matrix. Firstly we have calculated the asymmetry ratio between the separating matrix of the left and right class based on the euclidean matrix norm using a following mathematical formula [12]

$$\frac{\left\|W_L^f - W_R^f\right\|_2}{0.5 \times \left\|W_L^f + W_R^f\right\|_2} = \sigma_f \tag{9}$$

where σ_f is an asymmetry ratio/multiplier. The alpha and beta band asymmetry between the left and right classes will have the different values over subjects. The averaged alpha/beta asymmetry ratio (T_f) over the total number of subjects (N_s) can be estimated as

$$T_f = \frac{\sum_{n=1}^{N_s} \sigma_{fn}}{N_s} \tag{10}$$

where σ_{fn} is an asymmetry ratio/multiplier for the subject n. In order to satisfy the inequality in (8), we have to update the estimated separating matrix in such a way that it will achieve the desired inequality. The updated separating matrix can be written as

$$\begin{cases} {}^{New}W_L^f = T_f \times W_L^f \\ {}^{New}W_R^f = W_R^f \end{cases} \tag{11}$$

The updated separating matrix is used to estimate the corresponding frequency band components. The estimated frequency band components of left class and right class can be written as

$$S_i^f = {}^{New} W_i^f X_i^f \tag{12}$$

where

$$S_i^f = \begin{bmatrix} {}^1\mathrm{s}_i^f(1) & \cdot & \cdot & \cdot & {}^1\mathrm{s}_i^f(N) \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ {}^M\mathrm{s}_i^f(1) & \cdot & \cdot & \cdot & {}^M\mathrm{s}_i^f(N) \end{bmatrix} \equiv \begin{bmatrix} {}^1\boldsymbol{s}_i^f \\ \cdot \\ \cdot \\ \cdot \\ {}^M\boldsymbol{s}_i^f \end{bmatrix} \tag{13}$$

S_L^f and S_R^f are the estimated desired frequency band components when X_i^f is X_L^f and X_R^f in(4) respectively.

B. Feature Extraction

Many methods have been devised for the AR coefficient estimation but we concentrate on Burg's method for AR coefficient estimation because it provides stable, true characteristics for small data length. The AR coefficients were estimated from the EEG time series by a Burg's method and corresponding PSD were obtained from its frequency response. Each estimated desired frequency band components source ${}^k\boldsymbol{s}_i^f$ in (13) can be expressed as AR model of order P, which is given by the following equations

$${}^k\mathrm{s}_i^f[n] = -\sum_{\ell=1}^{P} a_\ell\, {}^k\mathrm{s}_i^f(n-\ell) + \xi(n) \tag{14}$$

where a_ℓ are the AR coefficients, $k = 1, \cdots, M$ and $\xi(n)$ is the uncorrelated white Gaussian noise having variance σ^2. Model can be characterized by the AR parameters. The PSD is given by

$$PSD(f) = \frac{\sigma^2}{\left|A(f)^2\right|} \tag{15}$$

where $A(f) = 1 + a_1 e^{-j2\pi f} + \cdots + a_P e^{-j2\pi fP}$, f represents the frequency components belongings to 0 to $\frac{f_s}{2}$, f_s is the sampling frequency. The model order P must be estimated before the AR spectrum can be computed. For estimating the model order we used Akaike information criterion (M_{AIC}) which is given by

$$M_{AIC}(P) = N_{AIC} ln\left(\sigma^2\right) + 2P \tag{16}$$

where $M_{AIC}(P)$ is minimized in order to estimate the model order P, N_{AIC} is the number of samples in the desired frequency band (8-30Hz). The feature vector $\boldsymbol{f}_j^i = [f_1^i, \cdots f_{N_f}^i]^T \in R^{N_f \times 1}$, $(j = 1 \cdots, N_t)$, where N_f is the number of feature variables and N_t is the total number of trials. We consider wide band spectral magnitude average as features because there are lateralized differences in spectral magnitude. Considering that differences, we propose the feature that is average of all spectral magnitude in the desired frequency band (8-30Hz)

Proposed feature I =Mean of the spectral magnitude (PSD) in the desired frequency band (8-30Hz)

The feature value is set as $f_k^i = E(PSD_k^i)$, $k = 1, \cdots, N_f$ and $i \in \{L, R\}$. Here E stands for average/mean of PSD magnitude in desired frequency band. PSD_k^i denotes the PSD of the k^{th} component of desired frequency band.

C. Linear Classifier

A literature related to classification algorithm [13] were surveyed and it was found that ample of existing classification algorithms were applied to design the BCI system. In this work we consider the LDA classification method based on linear least square methods as well as on Fisher criterion. We consider number of mental tasks (M_c) equal two. According to the equation $Y = \bar{\boldsymbol{f}}_j^{i^T} \boldsymbol{w}$ where $\bar{\boldsymbol{f}}_j^i = [f_1^i, \cdots f_{N_f}^i, 1]^T \in R^{(N_f+1)\times 1}$, $(i \in \{L, R\})$ $(j = 1 \cdots, N_t)$, N_t is the total number of trials, classifier weight parameter $\boldsymbol{w} = \left[w_1, \cdots, w_{N_f}, w_{N_f+1}\right]^T \in R^{(N_f+1)\times 1}$, linear classifier can assign a negative value to the feature vector $\boldsymbol{f}_j^L$ when $\boldsymbol{f}_j^L$ associates with the left imagery while positive value to the features vector $\boldsymbol{f}_j^R$ when $\boldsymbol{f}_j^R$ associates to the right imagery.

D. BCI performance parameters

In this paper work we consider the classification accuracy and Cohen's kappa coefficient as performance measure [14]. First of all we would like to describe the confusion matrix that shows relationship between the true class and the estimated class. The elements n_{ij} in the confusion matrix $\in R^{M_c \times M_c}$ indicate how many trials of class i have been predicted as class j. Accordingly the diagonal elements n_{ii} represents the number of correctly classified trials. The off diagonal n_{ij} represents how many trials of class i have been incorrectly classified as class j. The total number of trials $N_t = \sum_{i=1}^{M_c} \sum_{j=1}^{M_c} n_{ij}$.

The classification accuracy(ACC) or the error rate is the most widely used evaluation criteria in BCI research [14] . Now the classification accuracy p_0 can be defined as

$$ACC = p_0 = \frac{\sum_{i=1}^{M_c} n_{ii}}{N_t} \tag{17}$$

and the error rate $(ERR) = 1 - p_0$.

The winner of BCI competition IV on the Graze data set 2b had applied band pass filtering as preprocessing technique for EOG removal. They applied filter bank common spatial pattern (FBCSP) [4] for the feature extraction. And their classification techniques were Naive Bayes Prazen window classifier. They had obtained maximum average κ value 0.60.

The calculation of κ uses the overall agreement $p_0 = ACC$ which is equal to the classification accuracy and the chance agreement p_e [14]

$$p_e = \frac{\sum_{i=1}^{M_c} n_{:i} n_{i:}}{N_t^2} \tag{18}$$

where $n_{:i}$ is the sum of the elements of the i_{th} column and $n_{i:}$ represents the sum of the elements of the i_{th} row. Then the estimate of the κ is given by

$$\kappa = \frac{p_0 - p_e}{1 - p_e}. \tag{19}$$

The κ is zero if the estimated classes show no correlation with the actual classes. κ equals one indicates perfect classification.

III. Results and Discussions

The proposed method has been applied on the Graze data set 2b of the BCI competition IV. From training data we estimate firstly the updated separating matrix and secondly we estimate the linear classifier weight parameters for decision of belonging. The training data is firstly subjected to EOG correction. The EOG corrected EEG signals during 3s to 7.10s have been used for the feature extraction, which are passed through the bandpass (8-30Hz) FIR digital filter of order $L = 20$. The FIR filtered EEG signals are ensemble averaged and post processed by the AMUSE algorithm for estimating the separating matrix. The sampling frequency fs was 250Hz. In this paper work, we have selected the total number of samples N are 1024. The number of features variable (N_f) selected for feature extraction equals to 2 (corresponding to the largest singular value of time lagged covariance matrix). The number of channels M equals to 3. The total number of trials N_t for the training data is 160 (left imagery=80;right imagery=80) and for testing data is 160 (left imagery=80, right imagery=80) in each subject except subject B0204 (120 trials for training and testing each). We will use the 160 trials of training data to train the classifier and to estimate the updated separating matrix. The estimated separating matrix and classifier weight parameters are applied to the testing data for validation. The AR model order P was 16 as per discussion on section III.B.

Based on proposed feature and using equation (9) and (10) we obtain the $T_f = 2.80$ analytically. In order to get the best value of T_f, we have used the trial and error procedure. Experimentally we have chosen three different value of T_f and estimated the average classification accuracy 70.18 % for $T_f = 1$, 99.68% for $T_f = 2$ and 99.96% for $T_f = 3$. By tuning the $T_f = 1$ and $T_f = 3$ we have the following classification results over the training data which are shown in Fig.3 and Fig.2 respectively. In Fig.2 and Fig.3, F1

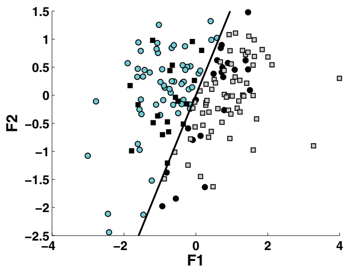

Fig. 2. The classification output when $T_f = 1$ over training data

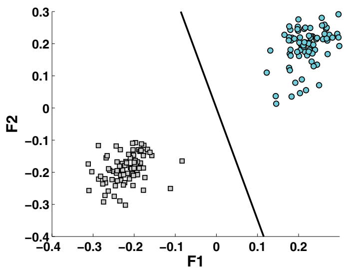

Fig. 3. The classification output when $T_f = 3$ over training data

corresponds to mean of spectral content of the first components of selected frequency band and F2 corresponds to mean of spectral content of second components in the same frequency band. The linear discriminant classifier separates the both class and marks with gray circle pattern for the left hand and gray square pattern for right hand movement imagination. The black circle points of Fig.2 indicate the misclassified feature vectors of the left class as the right class while the black squares points of Fig.2 indicate the misclassified feature vectors of the right class as the left class. From experimental results we obtained an asymmetry ratio $T_f = 3$ that provide almost 100% classification over the training data. Since the experimental and analytical values do not have a big difference. So we have chosen 3 as an asymmetry multiplier that is obtained from experiment. We have tabulated the results under original BSS method($OBSS$) and modified BSS ($MBSS$) in terms of the classification accuracy and Cohen's kappa coefficient. The reported results are not very good for all the subjects in comparison with the modified BSS ($MBSS$) method. The column of the subjects has two sets of data for each subject. The subject name BO103T has suffix T represents training

TABLE I
COMPARISONS IN TERMS OF CLASSIFICATION ACCURACY% WITH TWO DIFFERENT METHODS

Subject	$OBSS$	$MBSS$	$FBCSP$	$FBCSP$
B0103T	58.75	100	76.50	79.94
B0104E	47.50	100	-	-
B0203T	87.50	100	56.82	58.44
B0204E	81.67	100	-	-
B0303T	60.62	100	54.94	57.38
B0304E	70.63	100	-	-
B0403T	83.57	100	99.38	98.13
B0404E	95.63	100	-	-
B0503T	75.62	100	90.44	89.13
B0504E	57.50	100	-	-
B0603T	86.88	99.38	79.75	82.38
B0604E	88.75	100	-	-
B0703T	71.25	100	86.50	88.12
B0704E	66.25	100	-	-
B0803T	52.50	100	88.75	88.94
B0804E	63.12	100	-	-
B0903T	65	100	81.88	88.56
B0904E	50.62	100	-	-

TABLE II
COMPARISON OF COHEN'S KAPPA COEFFICIENT WITH BCI FIRST WINNER

Subject	$OBSS$	$MBSS$	BCI_{WIN}
B0103T	0.60	1	-
B0104E	0.65	1	0.40
B0203T	0.96	1	-
B0204E	0.88	1	0.21
B0303T	0.38	1	-
B0304E	0.31	1	0.22
B0403T	0.98	1	-
B0404E	0.98	1	0.95
B0503T	0.61	1	-
B0504E	0.20	1	0.86
B0603T	0.66	0.98	-
B0604E	0.85	1	0.61
B0703T	0.45	1	-
B0704E	0.33	1	0.56
B0803T	0.58	1	-
B0804E	0.42	1	0.85
B0903T	0.97	1	-
B0904E	0.78	1	0.74

data of subject B01 and B0103E has suffix E represents testing data of subject B01. B01 represents subject first. Similar kind of interpretations can be applied to all eight subjects. Table II shows the Cohen's kappa coefficient value obtained by the proposed method. The proposed method achieves maximum value of the Cohen's kappa coefficient unity in all subjects for training as well as testing data. The Cohen's kappa coefficient value is almost unity, so there is almost perfect classification. For the training data classification we applied 10×10 cross validation scheme while for the testing data uniform classification method was adopted in this work.

We compare our results in terms of the classification accuracy with two separate methods on the same datasets which are also listed in Table I, written as FBCSP and DFBCSP. The proposed method provides almost 100% classification accuracy in all subjects compared to the FBCSP and DFBCSP. We compare the results with the first winner of the BCI competitions IV on the same dataset in terms of Cohen's kappa coefficient. These values are listed in Table II. Our proposed method also outperforms over the first winner of the BCI competitions IV.

IV. CONCLUSIONS AND FUTURE WORK

In this study we propose a novel signal processing method for the three channels EEG signals/ more than three channels EEG signals. We incorporate the asymmetry property of the primary motor cortex areas of the human brain. The estimated asymmetry multiplier has been used to update the estimated separating matrix from the rhythmic components of the EOG corrected EEG signals. We have analyzed the three channels data and by proposed method we achieve almost perfect separation and also curtail the electrode placement time. This is the advantage of the proposed method. The disadvantage of the proposed method is that we have to collect many trials of the training data in order to estimate the separating matrix initially. In future study we will consider the left handed subjects. We will estimate the asymmetry multiplier and its effectiveness on the classification accuracy.

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