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FEATURE EXTRACTION AND CLASSIFICATION OF TWO-CLASS MOTOR IMAGERY BASED BRAIN COMPUTER INTERFACES

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ABSTRACT

Brain-computer interface (BCI) technology provides a means of communication for people with severe movement disability to communicate with the external world using the electroencephalogram (EEG). In this study, we propose a novel method for extracting the power information contained in specific frequency bands in the context of EEG based BCI. In a two-class Motor Imagery (MI) based BCI, the main objective is to filter EEG signals before feature extraction and classification to achieve higher classification accuracy. First the EEG signal is band-pass filtered in the range of 7Hz and 25 Hz and then the mu and beta rhythms are extracted as features. LDA is then applied as the classifier for classification of left and right motor imagery. It should be noted that the proposed method improves BCI performance when compared to the raw EEG signal.

KEYWORDS: Brain Computer Interface (BCI), Electroencephalography (EEG), Classification methods, BCI Research, Feature Extraction.

INTRODUCTION

A Brain Computer Interface (BCI) can be defined as a system which enables the user to act on his/her environment using their brainwaves without using the brain's normal output pathways which involves the peripheral nerves and muscles [1], [2]. The BCIs were designed with the initial intention of providing the ability to communicate to the handicapped population [2], [3]. The challenge in Motor Imagery-based BCI (MI-BCI), which translates the mental imagination of movement to commands, is the huge inter-subject variability with respect to the characteristics of the brain signals [4]. It backs up the belief of [5] claiming that the intention of BCIs was to enable people to converse with and control devices in the outside world without the use of traditional neuromuscular pathways thus bringing hope to those suffering from severe motor disabilities[6]. BCIs can also be used to operate devices such as prostheses enabling the paralyzed person to obtain direct brain control of a paretic limb, thus opening the way for rehabilitative and assistive applications [7]. It has been claimed that through certain mental actions our EEG can be regulated in such a way so as to operate a brain computer interface (BCI) which will change the EEG patterns into commands to allow the individual to operate devices such as prostheses [8].

However, it allows signals to be taken from the scalp and as they are non-invasive they are considered to be the safest and simplest way of recording the electrical activity of the brain [2]. As the signals recorded on EEG are recorded on the scalp they are more vulnerable to artifacts and power line interference that may be generated from muscular contractions, optical movements and other outside sources [9]. The removal of these artifacts or distortions from EEG signals before extracting features for classification of MIs is a useful step in order to increase signal-to-noise ratio (SNR) and also to obtain better separation of features of EEG signals corresponding to different imagined tasks [8].

One major challenge of this field is thus to extract reliable information from noisy data in real time in the form of relevant features [9]. These can then be passed on to classification techniques for identifying the user's mental state. Physiological arguments suggest that the μ and β frequency bands (around 8-12 Hz and 16-24 Hz) are especially relevant for discriminating motor activity. A common approach in the BCI field is thus to extract the power information from the signal over these frequency bands and use that as the classification feature.

In this paper, we propose a novel use of band-pass filtering method and then computing the band power feature information contained in different frequency bands of a real signal, in the specific context of motor imagery (i.e., limb movement imagination) for Brain-Computer Interfaces (BCI) [10]. The specificity of the BCI field is to deal with very noisy data captured by Electroencephalography (EEG). The goal is to infer the user's mental state from his/her EEG signals. In a BCI setup, the task is to find whether the user imagines left hand or right hand movements, in order to build an interactive Human-Computer interface based only on brain activity. Practical applications are envisioned for severely disabled people who cannot move their limbs but whose brain is still functional [2], [9].

MATERIALS AND METHODS

In this paper, we propose a use of band-pass filter between range of 7 Hz to 25 Hz to obtain enhanced EEG signals corresponding to the mu (μ) and beta (β) rhythms. The band power features are then computed from the enhanced EEG signals. These features are then classified into left and right hand MIs using an LDA classifier. The block diagram of the proposed method is shown in Fig. 1.

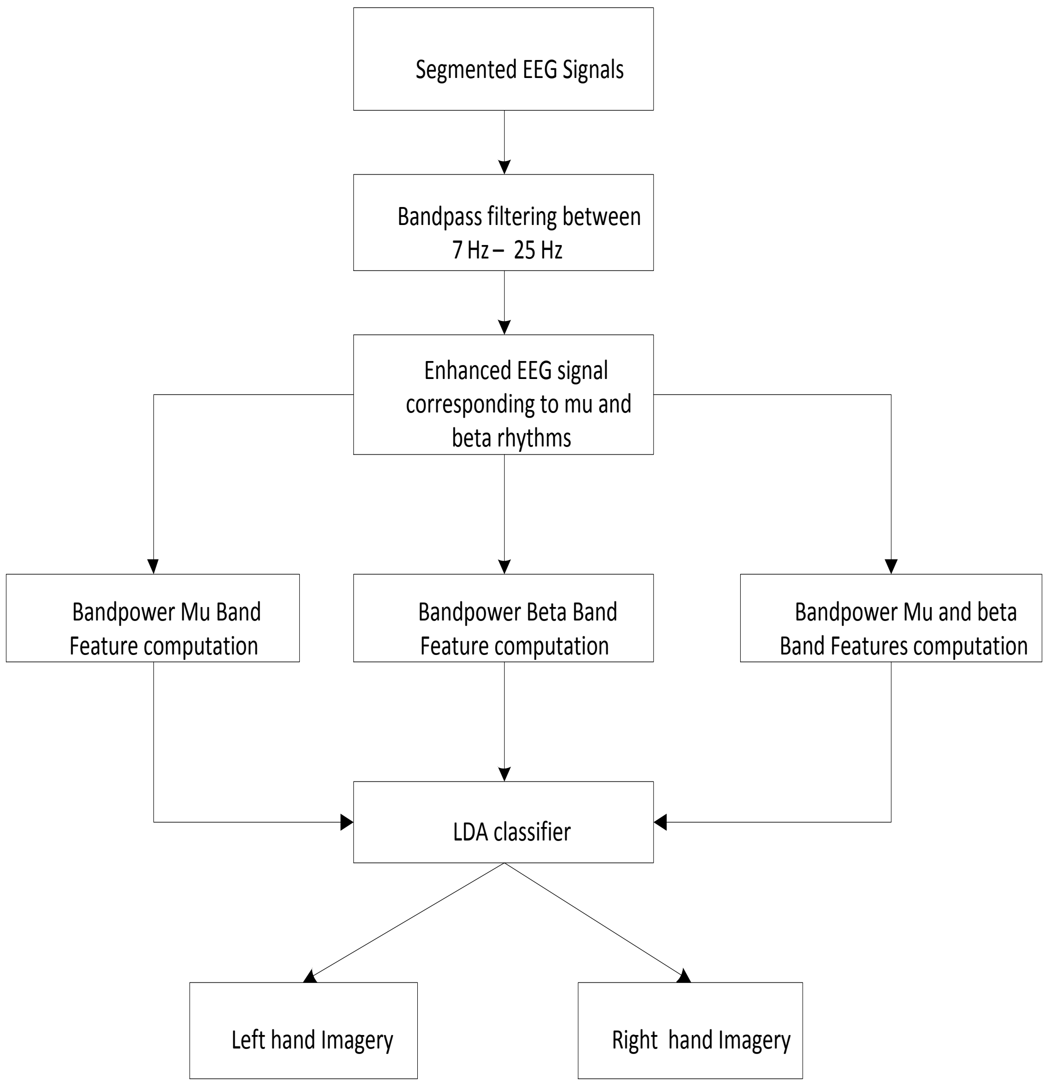

Fig. 1. Block diagram of the proposed method

In the below diagrams we show the raw EEG data and extracted enhanced EEG signal from the raw signal after applying band-pass filtering for the complete 8 second data with sampling frequency of 250 Hz.

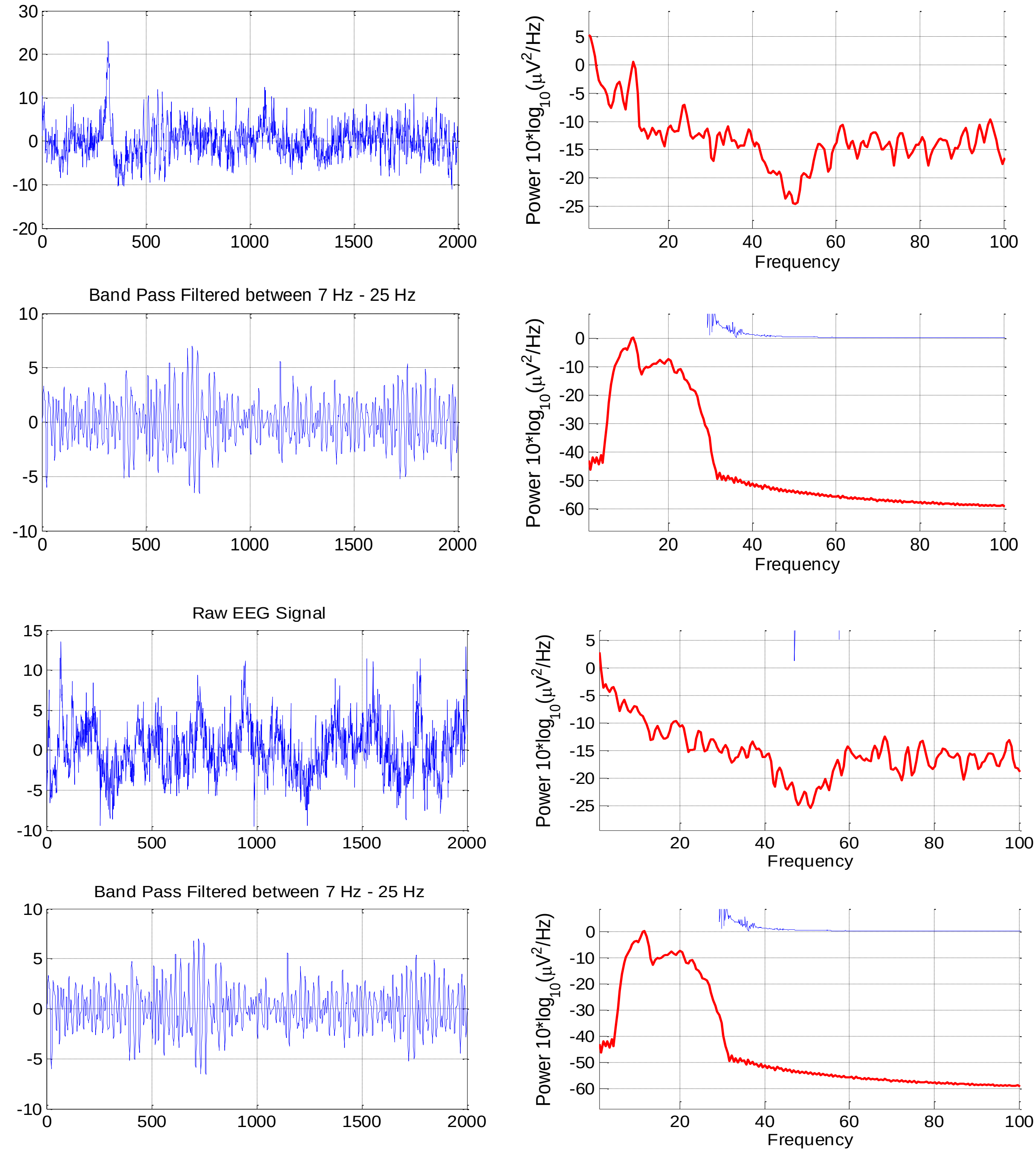

Fig. 2. The raw EEG data in trial #1 of channel C3 left hand and right hand Motor Imagery data and corresponding computed power in frequency domain and also after applying band-pass filtering between 7Hz to 25 Hz, and corresponding computed power in frequency domain.

FEATURE EXTRACTION

The process of feature extraction involves the extraction of signal features which will encode the intent of the user of the system [2]. As [9] explain in order to have an effective BCI operation the EEG features extracted should have a strong relationship to the intent of the user. The aim of feature extraction is to transform raw brain signals into a format which makes classification easier so that noise and other unwanted, unnecessary information is removed from the input signals while still retaining the information required to differentiate between different classes of signals [11], [12].

The main problem in all brain computer interfaces is the extraction of all signals which are of interest in the presence of a large number of biological and externally induced artifacts [12]. As [2] explain brain signals can become contaminated with electrical noise during the integration of BCI with robotics or functional electrical stimulation (FES). The possibility of artificial neural contamination is also possible if activities such as muscle movements or the movement of limbs are responsible for the activation of areas which are routinely used as sources of information for the BCI [7].

Band Power Features

Band Power is an estimation of the power information that is contained within different frequency bands of the EEG signals in a BCI interface. We have studied power extracted from three frequency bands known as mu feature, beta feature and mu + beta feature collectively. Feature mu is based on the EEG Mu rhythm which operates between 8-12 Hz and feature beta refers to the EEG beta rhythm which operates at a higher frequency of 16-24 Hz. Feature mu+beta uses a combination of frequency range 8-12 Hz and 16-24 Hz [11].

LINEAR DISCRIMINANT ANALYSIS (LDA) CLASSIFIER

It is a robust and linear classifier operating under the assumption that the different classes can be separated linearly. It gives a hyper plane to distinguish the features into two different classes. In general linear classifiers are more robust than their non-linear classifiers as they have limited flexibility and there is less chance of over fitting [13].

Generally, it is not straightforward to classify the extracted features for classification of EEG signals in BCI applications. Finding the optimum combination of the features which can provide better discrimination, is a crucial task. In this paper, we have used LDA classifier which is commonly used in EEG-based BCI applications. The LDA based classifier tries to reduce the dimensionality and at the same time it protects most of the class discriminatory information. Suppose, we have a set of two classes denoted by w_1, w_2. Then, we classify the *n*-dimensional sample points $x = \{x1, x2, x3, \dots \dots xn\}, n_1$ samples to the class w_1, and n_2 samples to the class w_2. In this method, we try to achieve a line $y = w^t x$ from the set of all possible lines, and that line maximizes the discrimination between the two considered classes. In order to obtain a good projection vector, we require to measure the separation between the two classes chosen for the study. The mean vector of each class in x-space and y-space is given by following equations:

$$\mu_i = \frac{1}{N_i} \sum\nolimits_{x \epsilon w_i} x \,, \tag{1}$$

$$and\, \tilde{\mu}_i = \frac{1}{N_i} \sum\nolimits_{y \epsilon w_i} y \; = \frac{1}{N_i} \sum\nolimits_{y \epsilon w_i} w^t x = w^t \mu_i \tag{2}$$

The objective function is defined as the distance between the two projected means. It can be expressed as follows:

$$J\,(w) \; = |\tilde{\mu}_1 - \tilde{\mu}_2\,| = |w^t (\mu_1 - \mu_2)| \tag{3}$$

However, the distance measured between projected means may not always be a good measure because the standard deviation between classes has not been considered. In order to overcome the limitation stated above, the enhancement of LDA has been proposed which is known as Fishers LDA classifier. It determines a decision boundary or probably a hyperplane in the feature space to classify the features in to distinct classes. It finds out the separation boundary between two given distributions in terms of ratio of two group variances as given below [3]:

$$J(w) = \frac{\sigma_{between}^2}{\sigma_{within}^2} = \frac{w^t(\mu_1 - \mu_2)^2}{w^t S_1 w + w^t S_2 w} \tag{4}$$

where μ_1, μ_2 are the mean of the classes and S_1, S_2 are the variances of the feature distributions between two classes w1, w2 respectively. The maximum separation between two classes can be shown by (10) as:

$$w^* = (S_1 + S_2)^{-1}(\mu_1 - \mu_2) \tag{5}$$

The w^* is weight vector which provides optimum direction of projection of the data. In the Fisher's LDA, the decision boundary uses the following equation to classify the feature vector d(m) as [14]:

$$\mathrm{p(m)} = \mathrm{d(m)}w^t + b \tag{6}$$

where b is the threshold or bias. The features are assigned to one of the classes based on the sign of the $\mathrm{p(m)}$.

RESULTS AND DISCUSSION

In this work, the BCI competition IV dataset 2B [15] has been used to measure the performance of the proposed method. The dataset contains EEG signals of two classes of three bipolar channels from 9 healthy subjects, denoted by B01-B09. In this dataset, for each subject 5 sessions has been provided. The data recorded from three bipolar channels include C3, Cz and C4 with a sampling frequency of 250 Hz [25]. In this paper, for training phase, a single session namely ^03T has been used. For the evaluation phase, we have used two sessions namely, ^04E and ^05E for computing the accuracy in the classification of left and right MI EEG signals. It should be noted that, the ^ in the session name denotes the subject number which ranges from B01 to B09. During the training session, we have performed a 5-fold cross validation in order to determine the time window for the best possible classification accuracy by the LDA classifier for classification of the left and right hand MI EEG signals.

In our work we have considered two frequency-bands namely 8-12Hz and 16- 24Hz corresponding to mu and beta bands. Hence band power features are computed in the selected frequency bands individually and collectively. The extracted features have been given as an input feature vector to the LDA classifier for classification of left and right hand MI EEG signals.

Table I depicts the maximum classification accuracy obtained for BCI competition IV dataset 2B with band-pass filtering, which provides the enhanced EEG signals between 7 Hz and 25 Hz for the nine subjects denoted by B01-B09 across three sessions 03T, 04E, and 05E.

Table I MAXIMUM CLASSIFICATION ACCURACIES OBTAINED IN MU BAND ON BCI COMPETITION IV DATASET 2B.

Subject	Accuracy with Band-pass filtering Mu(8 Hz -12 Hz) (%)			*Channel Selected*
	Training (03T)	***Evaluation (04E)***	***(05E)***	
B01	80.63	70	71.88	C3 C4 Cz
B02	80.63	79.17	65	C3 C4 Cz
B03	86.25	90	86.88	C3 C4 Cz
B04	81.88	80	80	C3 C4 Cz

B05	71.25	53.75	81.25	C3 C4
B06	71.88	71.88	64.38	C3 C4 Cz
B07	65.63	61.88	54.38	C3 C4 Cz
B08	88.75	93.75	93.13	C3 C4 Cz
B09	70.63	61.25	61.25	C4 Cz
Average	77.5	73.52	73.13	
Std	7.91	13.45	12.94	

As mentioned earlier, we have considered channels C3, C4 and Cz for calculating the results. In the training stage, after applying band-pass filtering, the average accuracy obtained across the nine subjects is 77.5 % with standard deviation of 7.91. In the evaluation stages, the average accuracies obtained in sessions 04 and 05 are 73.52 % and 73.13% respectively. Also, the standard deviations obtained are 13.45 and 12.94 respectively.

Table II MAXIMUM CLASSIFICATION ACCURACIES OBTAINED IN BETA BAND ON BCI COMPETITION IV DATASET 2B.

Subject	Accuracy with Band-pass filtering Beta(16 Hz -24 Hz) (%)			Channel Selected
	Training (03T)	**Evaluation (04E)**	**(05E)**	
B01	65.63	51.88	63.75	C4 Cz
B02	71.25	72.5	55	C3 C4
B03	93.13	90	86.88	C3 C4 Cz
B04	84.38	75.63	72.5	C3 C4 Cz
B05	59.38	50.63	64.38	C4
B06	56.88	68.13	59.38	C3 C4 Cz
B07	89.38	77.5	80.63	C3 C4 Cz
B08	86.88	84.38	76.25	C3 Cz
B09	88.75	88.75	93.75	C3 C4 Cz
Average	77.29	73.26	72.5	
Std	14.06	14.42	13.04	

As mentioned earlier, we have considered channels C3, C4 and Cz for calculating the results. In the training stage, after applying band-pass filtering, the average accuracy obtained across the nine subjects is 77.5 % with standard deviation of 7.91. In the evaluation stages, the average accuracies obtained in sessions 04 and 05 are 73.52 % and 73.13% respectively. Also, the standard deviations obtained are 13.45 and 12.94 respectively.

Table II shows the maximum classification accuracy obtained with band-pass filtering in the range of 7 Hz and 25 Hz for the nine subjects denoted by B01-B09 across three sessions 03T, 04E, and 05E for BCI competition IV dataset 2B. In the training stage, the average accuracy calculated across the nine subjects is 77.29 % with standard deviation of 14.06 and the average accuracy in evaluation session 04E is 73.6 % with standard deviation of 14.42 and in the evaluation session 05E is 72.5% with standard deviation of 13.04.

Table III depicts the maximum classification accuracy obtained for BCI competition IV dataset 2B for the enhanced EEG signals obtained with band-pass filtering in the range of 7 Hz and 25 Hz for the nine subjects denoted by B01-B09 across three sessions 03T, 04E, and 05E.

Table III MAXIMUM CLASSIFICATION ACCURACIES OBTAINED IN MU AND BETA BAND ON BCI COMPETITION IV DATASET 2B.

Subject	Accuracy with Band-pass filtering Mu(8 Hz -12 Hz) and beta (16 Hz-24 Hz) Collectively(%)			Channel Selected
	Training	**Evaluation**		
	(03T)	**(04E)**	**(05E)**	
B01	81.88	75	71.25	C3 C4 Cz
B02	80	72.5	68.75	C3 C4 Cz
B03	95.63	92.5	87.5	C3 C4 Cz
B04	85.63	85	79.38	C3 C4 Cz
B05	79.38	62.5	64.38	C3 C4 Cz
B06	76.25	71.88	65.63	C3 C4 Cz
B07	89.38	76.88	81.25	C3 Cz
B08	90.63	93.13	92.5	Cz
B09	91.25	86.88	89.38	C3 Cz
Average	85.56	79.58	77.78	
Std	6.55	10.38	10.68	

In the training stage, after applying band-pass filtering, the average accuracy obtained across the nine subjects is 85.56 % with standard deviation of 6.55. In the evaluation stages, the average accuracies obtained in sessions 04 and 05 are 79.58 % and 77.78% respectively. Also, the standard deviations obtained are 10.38 and 10.68 respectively.

The mu and beta bands feature collectively show higher classification accuracies with band-pass filtering, there is significant improvement of approximately 8% ($p<0.001$) of the maximum classification accuracy for all subjects across the training session 03T. In the evaluation sessions, with the feature combination of mu and beta bands the average classification accuracy improvement is > 6 % ($p < 0.001$) for 04E and in 05E, the average classification accuracy improvement is > 4 % ($p < 0.01$).

Fig. 3 displays the maximum classification accuracy obtained across all the nine subjects for training session 03T. The performance improvements across all the nine subjects using a combination of mu and beta band power features are illustrated with the bar graphs. In Fig. 4 and Fig. 5, the combination of mu and beta band power features shows an improvement in classification accuracy. In training session 03T, eight out of the nine subjects have shown significant improvement. On the other hand, in evaluation session 04E, five out of the nine subjects have shown improvement in the classification accuracy as compared to mu feature and beta feature independently and in 05E, with a combination of mu and beta, and improvement in classification accuracy ($p<0.01$).

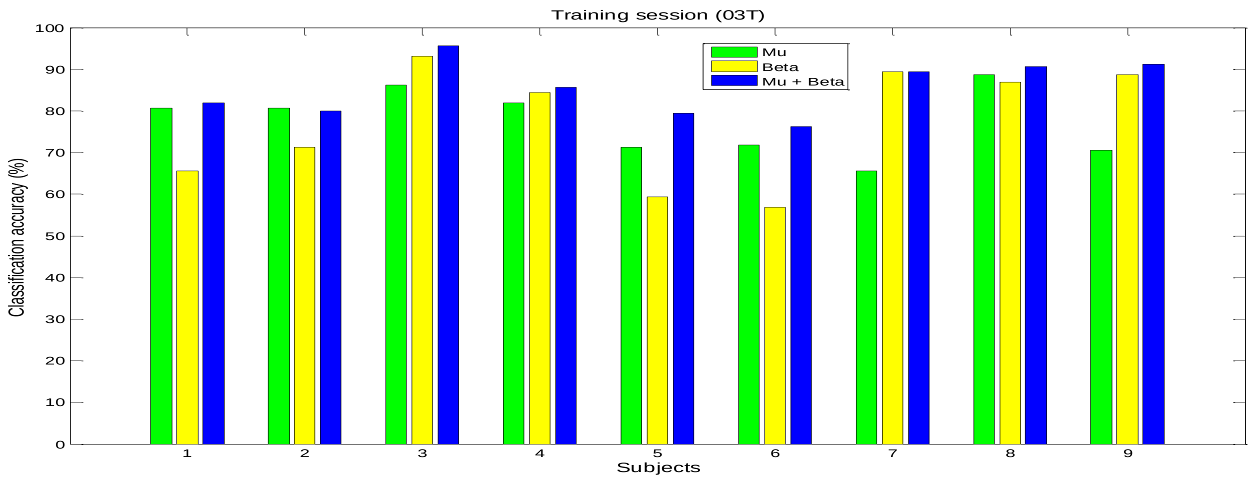

Fig. 3. Accuracy difference across all the features. The graph show an improvement of classification accuracy when we use collectively use mu + beta features in comparison to individual mu and beta features across training session (03T).

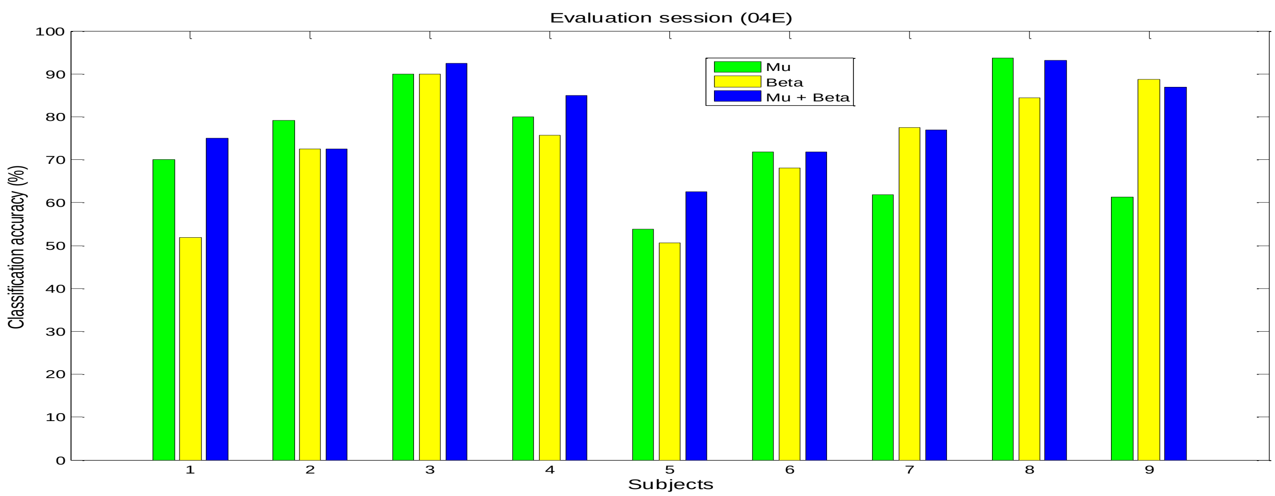

Fig. 4. The graph show an improvement of classification accuracy when we use collectively use mu + beta features in

comparison to individual mu and beta features across training session (04E).

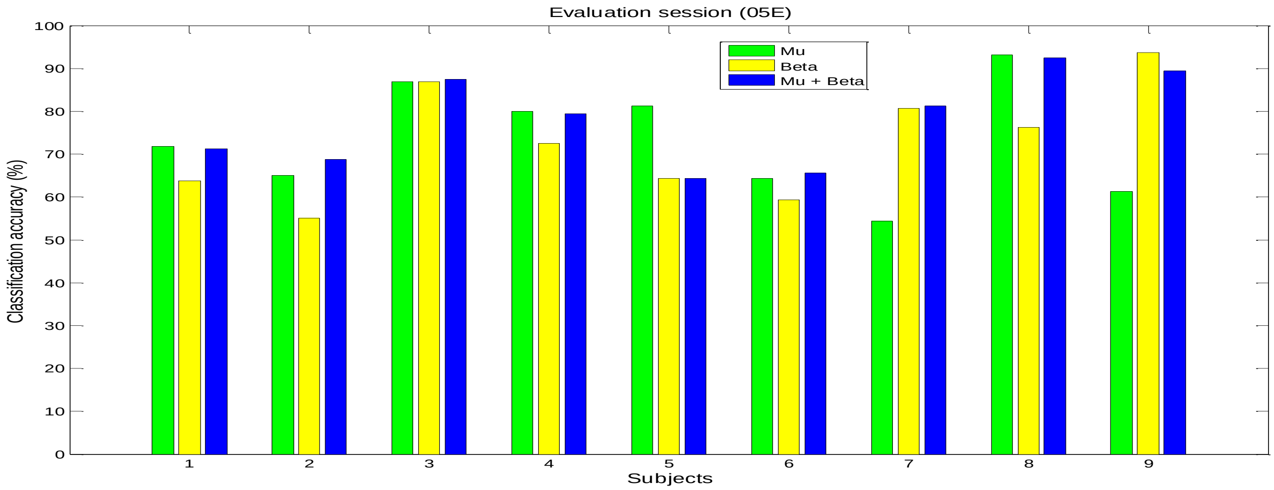

Fig. 5. The graph shows an improvement of classification accuracy when we use collectively use mu + beta features in comparison to individual mu and beta features across training session (05E).

CONCLUSION

We have applied band-pass filtering to extract the meaningful EEG data in order to correctly classify the left hand and right hand motor imagery task before feature extraction step. The filtering method help us to reduce the effect of artifacts and to enhance the performance of a motor imagery based brain-computer interface (BCI). A combination of features whose frequencies fall in the frequency range of μ and β rhythms has provided improvement in the accuracy of classifying left and right hand MI EEG signals as compared to μ and β feature individually. In future, it would be of interest to develop and implement new features along with the band-pass filtering method for classifying MI EEG signals. Although enhanced feature separability offered by the band-pass filtering method has helped to increase the classification accuracy by reducing the effect of artifacts.

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