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An Automatic Subject Specific Intrinsic Mode Function Selection for Enhancing Two-Class EEG based Motor Imagery-Brain Computer Interface

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***Abstract*—The electroencephalogram (EEG) signals tend to have poor time-frequency localization when analysis techniques involve a fixed set of basis functions such as in short-time Fourier transform (STFT) and wavelet transform (WT). These signals also exhibit highly non-stationary characteristics and suffer from low signal-to-noise ratio (SNR). As a result, there is often poor task detection accuracy and high error rates in designed brain-computer interfacing (BCI) systems. In this paper, a novel preprocessing method is proposed to automatically reconstruct the EEG signal by selecting the intrinsic mode functions (IMFs) based on a median frequency measure. Multivariate empirical mode decomposition (MEMD) is used to decompose the EEG signals into a set of IMFs. The reconstructed EEG signal has high SNR and contains only information correlated to a specific motor imagery task. The common spatial pattern (CSP) is used to extract features from the reconstructed EEG signals. The linear discriminant analysis (LDA) and support vector machine (SVM) have been utilized in order to classify the features into left hand motor imagery (LHMI) and right hand motor imagery (RHMI) tasks. Our experimental results on the BCI competition IV dataset 2A show that the proposed method with fifteen channels outperforms bandpass filtering with twenty-two channels ($> 1\%$) and by > 9 % ($p = 0.0078$) with raw EEG signals, $> 13\%$ ($p = 0.0039$) with empirical mode decomposition (EMD) based filtering and > 17 % ($p = 0.0039$) with discrete wavelet transform (DWT) based filtering.**

***Index Terms*—BCI, MEMD, filtering, common spatial pattern, linear discriminant analysis.**

I. Introduction

A brain-computer interface (BCI) is a system which facilitates a means of communication with external assistive devices utilizing brain signals such as electroencephalogram (EEG) [1]. In BCI, the aim is to translate the intent of a user into control command by EEG signals for a neuroprosthetics or a computer application. A popular example for a BCI modality is motor imagery (MI) based BCI [2], [3]. The user is expected to imagine the execution of a movement for a particular limb. Moreover, a rhythmic activity is seen in the sensorimotor cortex of the brain for a specific movement in MI-based BCI [4], [5]. The BCI systems identify these rhythmic activities and translate them into desired command. One of the major problems in EEG based BCI systems is the non-stationarity which arises when EEG signals are originating from different sources. In addition, the recorded EEG signals have a low signal-to-noise ratio (SNR)[6]. The low SNR may be due to artifacts resulting from electrooculogram (EOG) or electromyogram (EMG) interference and electrical power lines.

To increase the SNR, a useful step would be to remove these distortions or artifacts from raw EEG signals before extracting the features for classification [1]. An extension method based on common spatial pattern (CSP) has been studied to handle the adverse results of intervention from noisy EEG signals [7]. A Bayesian learning method has been implemented for spatial filtering in [8] for handling EEG signals with extremely low SNR. The methods built on the self-organizing fuzzy neural network (SOFNN) and the neural network (NN) concepts have also been proposed to attain better feature separation for MI tasks in MI-BCI [9], [10], [11]. Recently, a filtering technique based on quantum neural network has been proposed before the feature extraction step in [5] to gain better separation between classes. However, a univariate empirical mode decomposition (EMD) technique is also well suited for the analysis of non-stationary and non-linear signals [12], [13], [14]. This method is data dependent and adaptive in nature. It gives a group of intrinsic mode functions (IMFs). These are considered as narrow-band amplitude and frequency modulated (AFM) signals. Univariate EMD, however suffers from the problem of mode-mixing wherein similar frequencies occur in different IMFs [15]. To overcome this issue, a multichannel version namely, multivariate EMD (MEMD) has been investigated to show its comparative advantage [16], [15], [17], [18]. The MEMD allows to achieve high localization of information pertaining to specific frequency-bands. It decomposes the raw EEG signal into a finite set of frequency modulated (FM) and amplitude modulated (AM) components known as multivariate IMFs (MIMFs) [15]. It also provides the same number of IMFs for all the data channels in the time domain. It should be noted that the original MEMD decomposition method used visual inspection to discard the MIMFs [15]. Recently, a research group investigated several popular signal processing techniques, namely, EMD, discrete wavelet transform (DWT) [19] and wavelet packet decomposition (WPD) to classify multi-channel EEG signals into two classes ([20]. Moreover, EMD and DWT have been studied on a single ECG channel to extract respiratory waveforms [21].

In this work, a novel way to automatically select the subject specific MIMFs is proposed. The selected MIMFs are chosen based on the median frequency measure corresponding to mu and beta rhythms. These selected IMFs are summed to reconstruct EEG signal and remaining MIMFs are discarded. The detailed procedure for MIMF selection is provided by the algorithm II discussed in Section II .

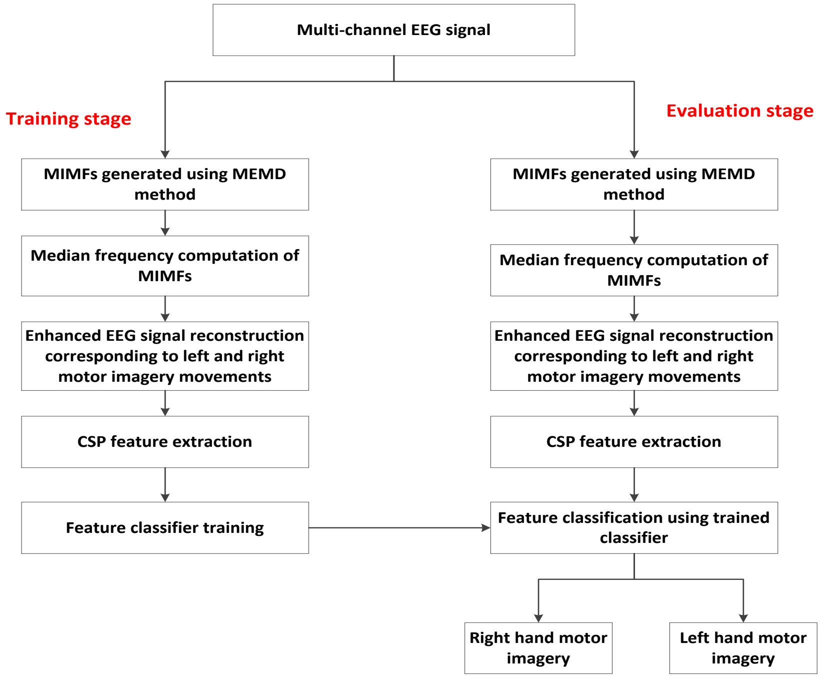

Fig. 1. Block diagram of the proposed methodology

Previously, a filtering technique was proposed [12] based on EMD which is restricted to decomposition of EEG signals on one channel at a time in MI-based BCI. Also, a multivariate extension of EMD based filtering was also proposed namely, MEMD based filtering [22], wherein mean frequency was utilized to identify the MIMFs with all the provided twenty-two channels but in this work only fifteen channels are used for studying the median frequency measure to automatically identify the subject specific MIMFs to reconstruct the enhanced EEG signals without compromising with the classification accuracy.

The aims of the paper are thus as follows:

1) To investigate the inter- and intra-subject non-stationarities persistent in the EEG signals;
2) To study whether the subjects have the different or same frequency components involved in MI task when EEG signals are measured from the same cortical areas;
3) Use median frequency measure to automatically find the subject specific MIMFs;
4) To find whether it is possible to achieve better classification accuracy using fewer monopolar EEG channels;
5) To report the classification accuracy when single trials are classified.

A block diagram representation of the proposed pipeline including MEMD based filtering with CSP features is shown in Figure 1. The remaining paper is organised as follows: In Section II, a brief introduction about the MEMD technique is discussed. The CSP features and details about the LDA classifier are discussed in Section III and Section IV. The results pertaining to the proposed method along with the discussion on those results and comparison with the methodologies developed by other research groups are discussed in Section V and finally, the paper concludes in section VI.

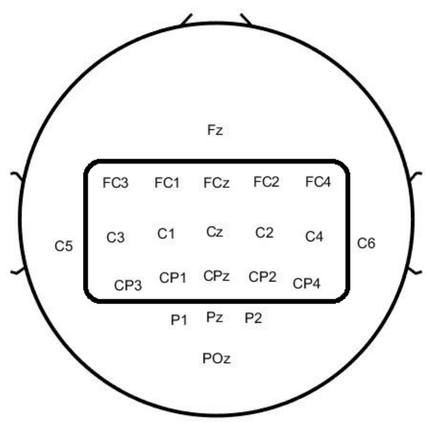

Fig. 2. Channels over the motor cortex used for the current study.

II. MULTIVARIATE EMPIRICAL MODE DECOMPOSITION (MEMD)

The EMD is a data driven technique to decompose a signal into a finite set of band limited basis functions called IMFs [23]. The MEMD has been developed recently where the local mean is computed by averaging the projection of the signal

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across multiple $n-$dimensional envelopes. The EEG signals tend to have poor SNR. They also suffer from interference from both EOG and EMG [24]. The EEG signals of interest corresponding to a particular movement (such as μ and β rhythms for motor imagery) may contain a lot of noise which leads to erroneous results. Therefore, a preprocessing technique is required to filter out the noise without weakening the original signal. In 1998, Huang et al. proposed EMD [23] which decomposes the original signal into a finite group of band limited basis functions which are known as IMFs, represented as follows:

$$Z(t) = \sum_{k=1}^{p} I_k(t) + Rd_p(t) \tag{1}$$

where $Z(t)$ denotes the actual signal in the time domain, $I_k(t)$ represents the k^{th} IMF, and $Rd_p(t)$ gives the residue. Thus, a summation of the selected IMFs can be done to reconstruct the signal of interest. Rest of the IMFs are discarded which may contribute to other artifacts and noise. However, univariate EMD suffers from the mode-mixing issue. To overcome this issue, another research group has proposed an ensemble empirical mode decomposition (EEMD) method [25]. Unfortunately, it is also not suitable for real-time implementations because it adds white noise to the signals and requires ensemble of many EMD methods which make this method very time-consuming. Further, a multichannel version of the EMD method has been proposed which utilizes cross channel information present across channels called MEMD [15], [26], [27], [28]. The mean $A(t)$ is computed through multivariate envelope curves, given as [29]:

$$A(t) = \frac{1}{p} \sum_{j=1}^{p} \mathrm{e}^{\theta_j}(t) \tag{2}$$

where j gives the length of vectors. $\mathrm{e}^{\theta_j}(t)$ denotes the multivariate envelope curves for the entire set of direction vectors. Further, the candidate IMF $Rd(t)$ by $Rd(t) = Z(t) - A(t)$ is computed. If the candidate IMF satisfies the stoppage criterion, then it becomes the multichannel IMF. Otherwise, we set the input $Z(t)$ equal to the remainder $Rd(t)$ and the complete process will be repeated again till remaining multivariate IMFs have been extracted. For more details refer to [15].

The contribution of this work is to automatically select the subject specific MIMFs for a particular subject corresponding to μ and β rhythms and then perform the summation of selected MIMFs. In order to select the MIMFs, the median frequency measure has been calculated for all MIMFs corresponding to the LHMI and RHMI. The median frequency of each IMF is calculated as half of the total power of IMF in the frequency domain [30]. The mathematical expression of median frequency is given as,

$$MDNF_{IMF} = \sum_{i=1}^{MDNF} P_i = \sum_{i=MDNF}^{n} P_i = \frac{1}{2} \sum_{i=1}^{n} P_i \tag{3}$$

where n denotes the length of frequency bin, and P_i gives the total power of IMF in the frequency domain. These computed median frequencies of each IMF represent frequency at which the IMF power spectrum is divided into two regions having equal amplitude in the spectrum in frequency domain. The median frequency was used to first automatically identify the subject specific MIMFs providing major contribution to μ and β rhythms. Thereafter, the selected MIMFs are summed to reconstruct the enhanced EEG signals corresponding to the LHMI and RHMI. The reconstructed EEG signals contains information which provides major contribution to mu (μ) (8-12 Hz) and beta (β) (16-24 Hz) rhythms observed over the central region of the brain when the subjects plan or execute hand movements. The features extracted from the reconstructed EEG signals are used for classification of LHMI and RHMI tasks.

Algorithm 1 Proposed pre-processing algorithm

Input: Let X denotes the signal in time domain
Output: Enhanced EEG signal in time domain

```
for each trial
MIMFs=memd(X)
Compute median frequency(mf) for each MIMF
if (mf > 6 and mf < 24 ) then
    MIMFx is/are selected.
else
    MIMF is discarded.
end if
Filtered_signal=sum(MIMFx)
return Filtered_signal
```

III. Common spatial pattern (CSP)

CSP features are calculated by utilizing the CSP algorithm from selected fifteen channels corresponding to MI-based BCI (Fig. 2). The CSP algorithm may be understood as a method which generates weight maps of the selected channels for EEG signals. These weight maps provide the importance of EEG signal content of the channels for separating the two conditions present in the data [31], [32]. These weight maps are spatial filters which are then projected onto data. With the projection of these spatial filters, the data is altered in such a way that the ratio of the variance for EEG amplitudes between the given two conditions is maximized. Therefore, the variance of the filtered EEG signal may serve as a discriminative feature for a two-class classification problem. The scalp potentials of the recorded EEG signal may not have good spatial resolution. One possible reason may be the volume conduction problem. With the poor spatial resolution, the EEG signal classification task becomes tougher if other sources give stronger signals when compared to the required signal in the specified frequency range [31].

As mentioned in Section I, the CSP algorithm has shown promising results in computing spatial filters for detecting event related desyncronization / event related synchronization (ERD/ERS) [31], [33]. It is a trial specific supervised decomposition of signals which is parameterized by a projection matrix $PM \in \Re^{Chn \times Chn}$ where Chn denotes the number of channels selected. In EEG signal sensor space, PM gives the

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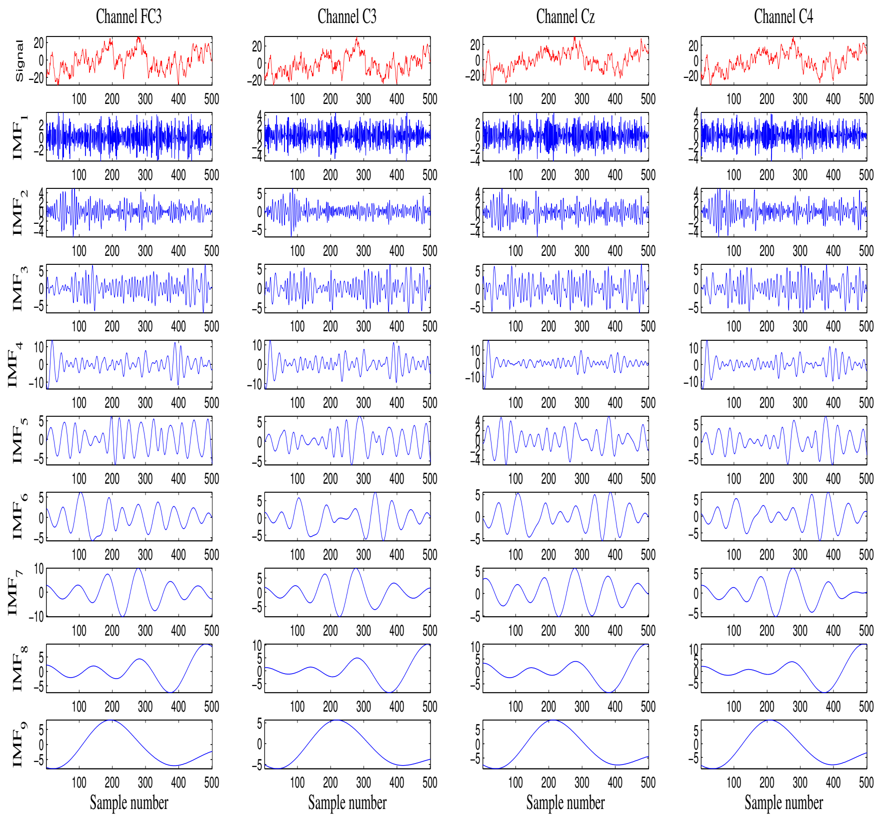

Fig. 3. The EEG signal corresponding to channels FC3, C3, Cz, and C4 of the trial 1 of A08T for the LHMI task and its first nine IMFs.

projection of a single trial $Tr \in \Re^{Chn \times t}$ to $C \in \Re^{Chn \times t}$ in the surrogate sensor space, which is represented as:

$$C = (PM)^T \times Tr \tag{4}$$

where Tr gives $Chn \times t$ EEG measurement data from a single trial, obtained from Chn EEG channels sampled t times. The spatial filters are denoted by the rows of PM.

The spatially filtered signal C provided in (4), maximizes the ratio of the variances of the two classes. A CSP analysis is employed to obtain an efficient discrimination between two different conditions which are described by ERD/S phenomena. However, the variances concerning to a small subset of spatial filters are usually selected. The first M and last M rows of C i.e., C_e , $e \in \{1, 2, ..., 2M\}$ given in (4) are used. In this study, we have considered $M = 5$ spatial filters. For more details, refer to [31].

IV. Classification

Generally, it is a demanding task to find the best feature combination which can reduce classification errors and provide better feature separability [34]. The LDA classifier and SVM classifier with linear kernel have been applied in this work, which is most popularly used on EEG signals for BCI applications. It reduces the dimensionality of the feature set and also preserves the maximum information required for class discrimination.

V. Results and Discussion

The BCI competition IV dataset 2A [33], [35] has been used for this study. This dataset contains EEG signals recorded from nine healthy subjects, namely, A01-A09 for left hand, right hand, feet, and tongue MI tasks. The effectiveness of the proposed preprocessing technique has been evaluated on LHMI and RHMI tasks in all nine subjects. Each subject's EEG data is recorded over two sessions, e.g., A01T and A01E [33], [35]. In this paper, only fifteen channels (i.e., FC3, C3, CP3, FC2, C2, CP2, FC1, C1, CP1, FCz, Cz, CPz, FC4, C4 and CP4) are considered for analysis from the available twenty-two channels as shown in Figure 2. More details on this dataset can be obtained from [35]. For the computation of classification accuracy (in %) for each subject, 100% of A0ST data has been considered for training the classifier model using an LDA classifier. Then, it is evaluated on 100% data A0SE of the evaluation session, where S represents the subject number. In the MI paradigm, the MI task begins at 2 second; the training session and evaluation session features have been extracted from the 2.5 to 4.5 seconds time interval similar to the competition winner [33].

During the training session, a five-fold cross-validation has been applied to classify the EEG signals into LHMI and RHMI tasks. To demonstrate the decomposition dynamics of the MEMD technique, single trial EEG signals per class are

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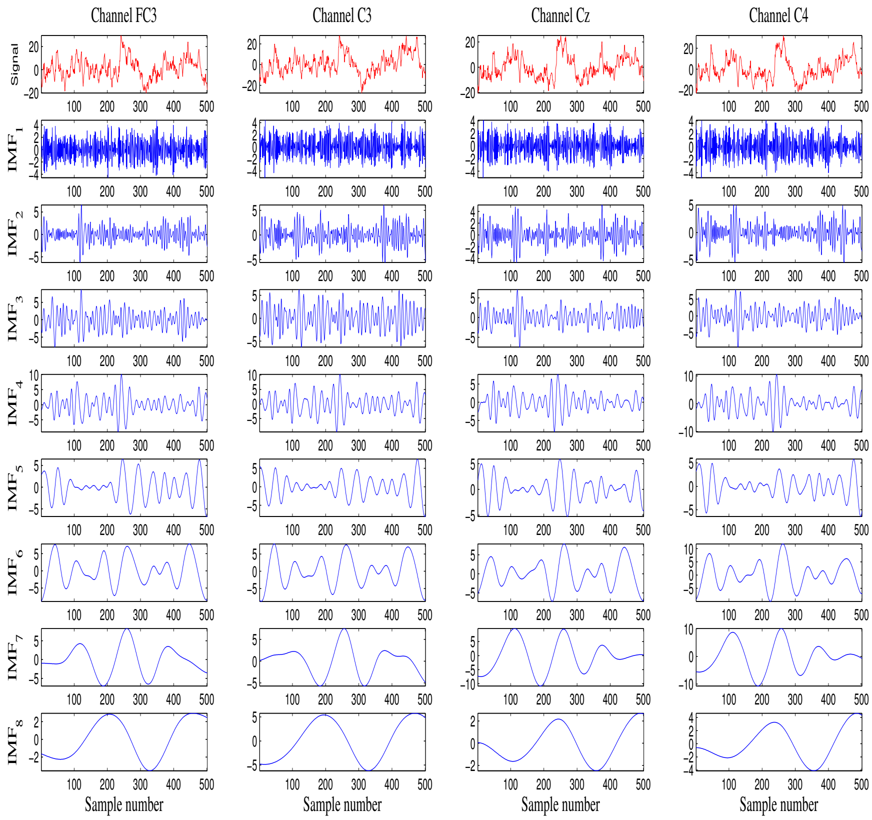

Fig. 4. The EEG signal corresponding to channels FC3, C3, Cz, and C4 of the trial 1 of A08T for the RHMI task and its first nine IMFs.

considered from the subject A08's training session data A08T. Figure 3 demonstrates the LHMI tasks, raw EEG signals and its obtained IMFs whilst Figure 4 gives the RHMI EEG signal and its obtained IMFs. The statistical mean frequency measure has been computed for each of the IMFs obtained pertaining to LHMI and RHMI tasks. To get enhanced EEG signals pertaining to these MI tasks, the IMFs are first identified based on mean frequencies which lie in the frequency range $4-33$ Hz [12]. This frequency range comprises the mu (μ) band and beta (β) band. These bands play a critical role in the identification of MI EEG signals [5], [36], [12].

Figure 5 and Figure 6 display the feature distribution of four features. The box plot in Fig. 5 represents the four features using the Kruskal-Wallis test with the MEMDBF method. To show the effect of the proposed method on the available features, feature separability is evaluated using the Wilcoxon test method for the LHMI and RHMI tasks. The features are arranged in decreasing order of class separability. The proposed preprocessing method has thus helped achieve statistically significant improvement in feature separability ($p < 0.005$) in training session for the LHMI and RHMI tasks. Figure 6 displays the same four features from the raw EEG signals giving p-values of 0.0250, 0.3816, 0.1572, and 0.0046. These p-values reveal the fact that the two features are not significantly different in their feature distribution for the LHMI and RHMI tasks. However, with the proposed pipeline, the p-values show a statistically significant difference in feature distribution for all four features. The subject A01 was used for computing results. The non-parametric Wilcoxon test is used for ranking the four features.

Table I illustrates the specifics of the rejected trials in the evaluation session from each subject marked with the event 1023 [35]. Subjects A04 and A06 have maximum number of the rejected trials. Subject A04 has a total 28 rejected trials while Subject A06 gives a total of 36 rejected trials. The rejected trials pertaining to right hand and left hand MI tasks across all nine subjects are as follow: right hand 58 trials and left hand 55 trials respectively. A subject specific rejected trials across all the nine subjects can be obtained from Table I.

TABLE I
REJECTED TRIALS FROM ALL SUBJECTS

Subject	Total Trials	Correct Trials	Rejected Trials	Left hand	Right hand
A01	144	141	3	1	2
A02	144	142	2	1	1
A03	144	137	7	5	2
A04	144	116	28	13	15
A05	144	135	9	2	7
A06	144	108	36	19	17
A07	144	140	4	1	3
A08	144	134	10	6	4
A09	144	130	14	7	7

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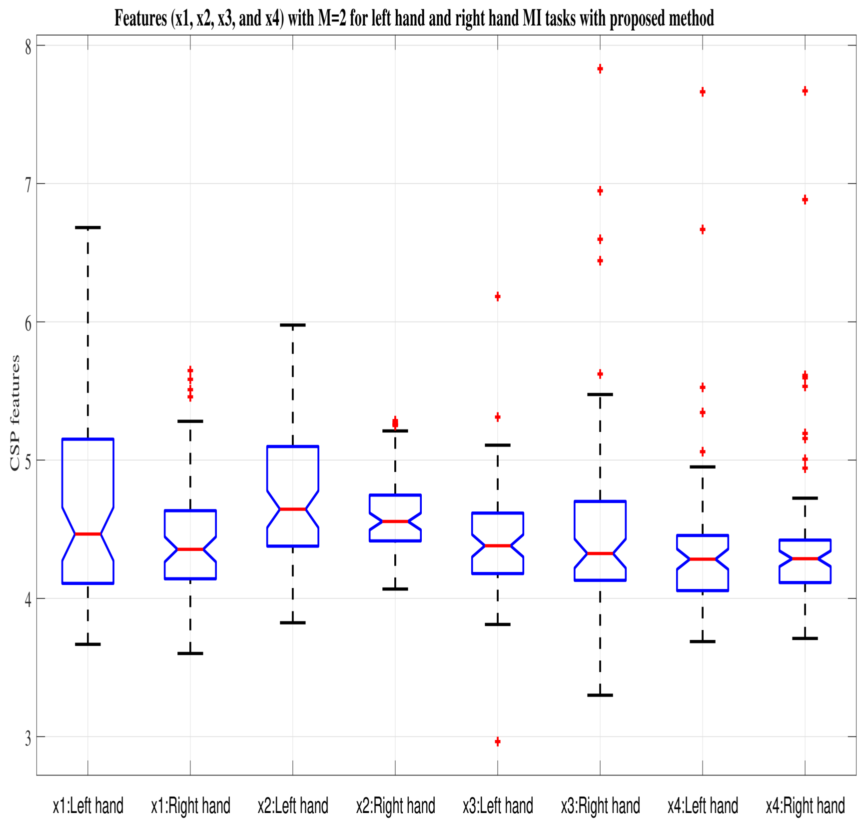

Fig. 5. The box plot displays the calculated four features using MEMDBF in the training session for left hand and right hand MI tasks.

Table II shows the classification accuracy and precision for the BCI competition IV dataset 2A obtained using LDA classifier and SVM [37] classifier (linear kernel) with the proposed method. This method provides enhanced EEG signals for all A01-A09 subjects as compared to raw EEG signals, EMD based filtering and DWT based filtering, across two sessions namely, the training and evaluation sessions. This pre-processing step has helped to achieve a classification accuracy of 79.19% with LDA classifier and 79.18% with SVM classifier (linear kernel) in the evaluation session. Moreover, the classification accuracy was computed using other kernel functions as well such Additionally, the precision obtained is 79.88 and 80.22 using LDA and SVM classifier respectively.

Table III presents the comparison of the classification results obtained using the proposed method, raw EEG signals and other filtering techniques such as EMD based filtering and DWT based filtering. With the enhanced EEG signals using the MEMDBF method, the group average of classification accuracy improved by 6.68% as compared to raw EEG signals, 6.87% as compared to EMD based filtering and 11.49% as compared to DWT based filtering across all subjects considering both training and evaluation sessions. Evaluation accuracy has been computed with a classifier model created using 100% training session data. The results computed in the training session clearly depict that the average of the classification accuracy improved by 4.01% $(p = 0.0742)$ with a standard deviation of 11.86 with the MEMDBF-CSP method compared to the raw EEG signals considering the same features. The proposed method also helped to achieve an average group improvement of $> 5\%$ as compared to DWT based filtering in the training session. Notably, eight of the nine subjects have improved in classification accuracy in the evaluation session when compared to other filtering techniques and raw signals. Also the group average of classification accuracy across all nine subjects has improved by > 9 % $(p = 0.0078)$ with raw EEG signals, > 13 % $(p = 0.0039)$ with EMD based filtering and > 17 % $(p = 0.0039)$ with DWT based filtering respectively. The proposed method was able to select the IMFs which were contributing to the specific bands.

With the proposed method, the difference between accuracies obtained in the training session and evaluation session have been very minimal (>3 %). As discussed, the training session accuracies have been computed using a five-fold cross-validation mechanism. Evaluation accuracies in Table III has been computed by creating a learning model with 100% of the training session data. Subjects A01, A03, A08, and A09 have obtained greater classification accuracy in the evaluation session as compared to the training session accuracies. In the column Evaluation, Subjects A02, A04, A05, A06, and A07 have a difference of $< 8.5\%$ in terms of classification accuracy across training and evaluation sessions. Thus, the results clearly show the proposed pipeline has helped to

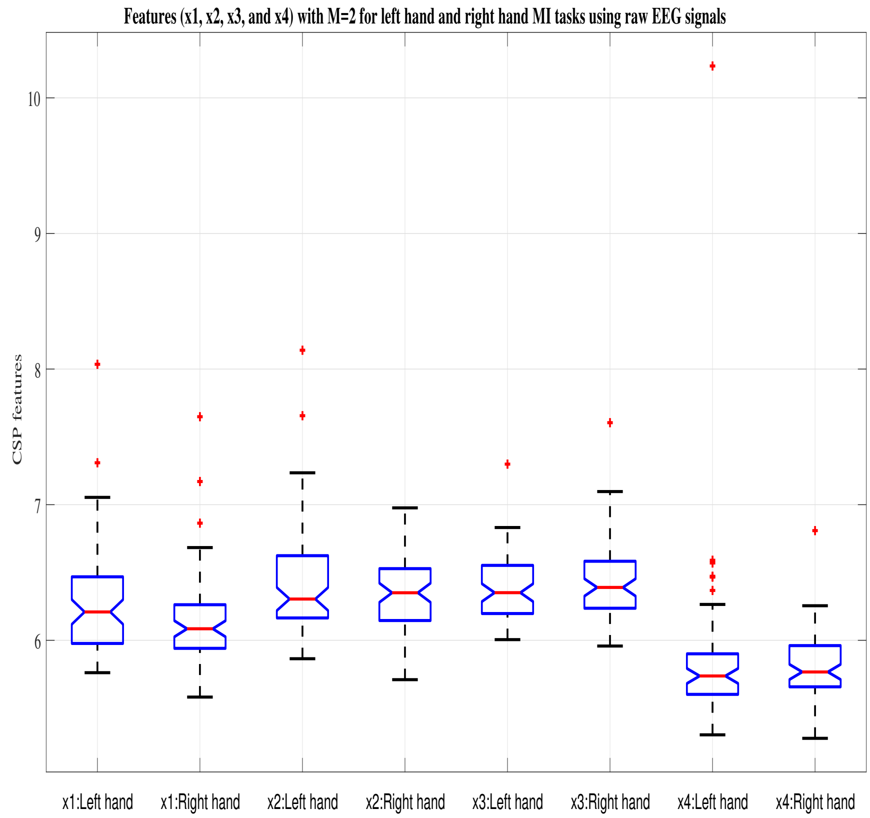

Fig. 6. The box plot reveals that the same four features from the raw EEG signals are not statistically significant in terms of separability with p-values (0.0250, 0.3816, 0.1572 and 0.0046).

TABLE II
CLASSIFICATION ACCURACIES (IN %) OBTAINED WITH THE PROPOSED MEMDBF METHOD AND RAW EEG SIGNALS BY LDA AND SVM CLASSIFIERS EVALUATED ON BCI COMPETITION IV DATASET 2A.

Subject	MEMDBF-CSP							
	LDA				SVM(Linear Kernel)			
	Accuracy		Precision		Accuracy		Precision	
	Training	Evaluation	Training	Evaluation	Training	Evaluation	Training	Evaluation
A01	90.28	90.78	88.7	93.94	89.48	91.49	100	94.03
A02	65.28	57.75	65.16	55.45	61.9	59.86	76.92	57.95
A03	93.75	97.08	93.35	97.01	90.96	94.89	84.62	96.88
A04	74.31	70.69	69.81	68.66	72.11	70.69	57.14	75.51
A05	68.06	61.48	66.74	65	59.04	60.74	57.89	66.67
A06	78.47	70.37	78.64	69.09	73.62	67.59	76.92	66.07
A07	79.86	72.14	78.59	75.81	78.53	75	80	69.57
A08	97.22	97.76	95.14	95.65	96.57	97.76	100	97.01
A09	93.75	94.62	93.1	98.33	93.03	94.62	92.86	98.33
Average	82.33	79.19	81.03	79.88	79.47	79.18	80.71	80.22
Std	11.86	15.85	11.98	16.42	13.8	15.49	15.86	16.18

TABLE III
CLASSIFICATION ACCURACIES (IN %) OBTAINED WITH THE PROPOSED MEMDBF METHOD AND RAW EEG SIGNALS BY LDA CLASSIFIER EVALUATED ON BCI COMPETITION IV DATASET 2A.

Subject	MEMDBF-CSP		Raw EEG Signal		EMD-CSP		DWT-CSP	
	Training	Evaluation	Training	Evaluation	Training	Evaluation	Training	Evaluation
A01	90.28	90.78	72.27	69.44	84.01	68.79	70.17	53.19
A02	65.28	57.75	63.21	50	73.62	49.3	70.81	50
A03	93.75	97.08	91.65	90.28	89.48	81.75	76.96	64.96
A04	74.31	70.69	71.58	59.03	77.14	54.31	70.81	53.45
A05	68.06	61.48	67.92	50	74.39	51.85	73.67	51.85
A06	78.47	70.37	67.99	54.86	77.73	58.33	71.57	49.07
A07	79.86	72.14	86.18	65.28	75.02	45	82.66	60.71
A08	97.22	97.76	95.19	97.92	95.12	92.54	86.89	80.6
A09	93.75	94.62	88.86	91.67	93.12	88.46	90.91	88.46
Average	82.33	79.19	78.32	69.83	82.18	65.59	77.16	61.37
Std	11.86	15.85	12.04	18.82	8.47	17.95	7.8	14.22
***p*-value**				0.0078		0.0039		0.0039

TABLE IV
COMPARISON OF CLASSIFICATION ACCURACIES (%) OBTAINED WITH THE PROPOSED MEMDBF METHOD AND OTHER STATE-OF-THE-ART METHODS EVALUATED ON BCI COMPETITION IV DATASET 2A.

Subject	MEMDBF-CSP	Method-1	Method-2	Method-3
A01	**90.78**	88.89	90.28	90.28
A02	**57.75**	51.39	54.17	57.64
A03	**97.08**	96.53	93.75	95.14
A04	**70.69**	70.14	64.58	65.97
A05	**61.48**	54.86	57.64	61.11
A06	70.37	**71.53**	65.28	65.28
A07	72.14	**81.25**	62.5	61.11
A08	**97.76**	93.75	90.97	91.67
A09	**94.62**	93.75	85.42	86.11
Average	79.19	78.01	73.84	74.92
Std	15.85	17.01	15.93	15.42
***p*-value**		0.2852	0.0039	0.0039

counteract the inherent intersession non-stationarity present in the EEG signals. This difference in the classification accuracy across evaluation sessions in all subjects may be accounted with the adaptive techniques/ transfer learning mechanisms.

Table IV presents the comparison of classification accuracy values calculated with the MEMDBF-CSP method and other comparable works in the literature. The proposed MEMDBF-CSP has shown comparable performance with one approach reported in [38] and substantial improvement when compared to other research works reported in [39]. The superior average classification accuracy has been achieved across nine subjects in comparison to results reported by four most recent advanced methods. The method-1 [38] reported 78.01% (p = 0.2852), method-2 [39] obtained 73.84% (p = 0.0039) and method-3 [39] reported 74.92% (p = 0.0039). The Wilcoxon signed rank test has been used to compute the p-values. These methods investigated the same two-class classification problem to classify the LHMI and RHMI tasks but there is a slight variation in the number of channels. Using the method-1, twenty-two channels raw EEG signal was bandpass-filtered between 8-30 Hz and further the CSP features with a number of components (nc=3) were extracted. Thereafter, the features set was calculated by taking the log variance of three pairs of selected filters. Finally, they classified the feature set by an LDA classifier [38]. The method-1 considered all twenty-two channels(nch =22) to compute the classification accuracy while comparable results are obtained with the MEMDBF-CSP method using only fifteen channels(nch =15). Method-2 and method-3 used only ten channels (nch =10) for the study. They extracted CSP features from the bandpass filtered ten EEG channels and further only 1 component (nc=1) was selected from the CSP features. They detected the covariate shift in the feature matrix and then applied adaptive learning and transductive learning to adapt to the covariate shifts [39]. Their method performs adaptation by updating the classifier in the evaluation stage. More details can be obtained from [39]. The MEMDBF-CSP thus demonstrates a tangible improvement in classification accuracy for seven of the nine subjects as marked in boldface in Table IV.

VI. CONCLUSION

A pipeline, namely, MEMDBF-CSP has been proposed to enhance performance in MI-based BCI with a minimal number of channels. This pipeline has the MEMDBF method as a preprocessing step which is an extension of the MEMD. In the second step of this pipeline, CSP features have been implemented for enhancing the performance of a two-class MI-based BCI. The key idea in the proposed pipeline is that at the preprocessing stage, MEMD based filtering removes inherent non-stationarity present in EEG signals to some extent whilst filtering artifacts and noise. The enhanced EEG signals have zero mean. There is no complexity introduced at the feature extraction step or the classification step. A highly significant performance has been obtained in MI-based BCI simply by enhancing the EEG signals at the pre-processing stage. A selection of multiple IMFs based on the median frequency measure which lie in the frequency range of the mu and beta bands, helped gain improvement in classification accuracy, while classifying LHMI and RHMI-based EEG signals as compared to raw EEG signals with CSP features. The classification accuracy obtained from this pipeline has shown significant improvement through both the training and the evaluation sessions across multiple subjects. The MEMDBF with CSP features has thus shown superior performance in classification accuracy not only when compared to raw EEG signals, but also when compared with similar advanced techniques such as adaptive learning. An improved feature separability was achieved using this pipeline. As a result, non-stationarity present in the EEG signal has been handled to a good extent. Future work may include proposing automated computational methods such as a genetic algorithm (GA) or particle swarm optimization (PSO) for selecting a subject specific channel combination or parameters, which may further increase performance. It may also be interesting to evaluate the performance of pre-processing stage with hidden Markov model (HMM) or long short-term memory (LSTM) networks.

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