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Original Article

A New Design of Mental State Classification for Subject Independent BCI Systems

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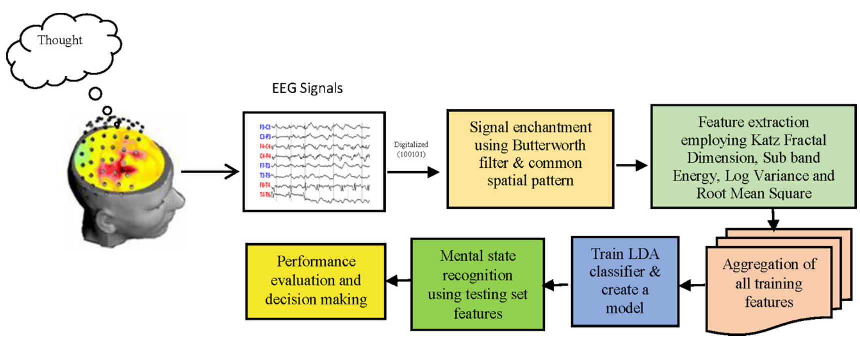
HIGHLIGHTS

- A novel SI based BCI framework is introduced to identify mental states.
- A new channel selection concept is also proposed for SI based BCI system.
- Efficacy of the method is confirmed by statistical and graphical analyses.
- The proposed method outperforms the existing methods.
- This design will help to build up a new technology for development of SI based BCI.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Brain Computer Interface (BCI) systems have been widely used to develop sustainable assistive technology for people suffering from neurological impairments. A major limitation of current BCI systems is that they are based on Subject-dependent (SD) concept. The SD based BCI system is time consuming and inconvenient for physical or mental disables people and also not suitable for limited computer resources. In order to overcome these problems, recently subject-independent (SI) based BCI concept has been introduced to identify mental states of motor disabled people but the expected outcome of the SI based BCI has not been achieved yet. Hence this paper intends to present an efficient scheme for SI based BCI system. The goal of this research is to develop a method for classifying mental states which can be used by any user. For attaining this target, this study employs a supervised spatial filtering method with four types of feature extraction methods including Katz Fractal Dimension, Sub band Energy, Log Variance and Root Mean Square (RMS) and finally the obtained features are used as input to Linear Discriminant Analysis (LDA) classification model for identifying mental states for SI BCI system.
Results: The performance of the proposed design is evaluated in several ways such as considering different time window length; different frequency bands; different number of channels. The mean classification accuracy using Katz feature is 84.35% which is the maximum output compare to other features that outperforms the existing methods.

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Conclusions: Our proposed design will help to make a new technology for development of real-time SI based BCI systems that can be more supportive for the motor disabled patients.

1. Background

Recently, brain computer interface (BCI) has become popular as a new frontier in assistive technology for helping severe motor disabled peopleto improve their quality of life [1]. The BCI is a new communication way that allows person with motor disabilities to communicate with their environment and control prosthetic or other external devices by using only their brain activity [2,3]. BCI read electrical signals of brain activity and translate them into a digital form and then analyze them, and convert them into commands that are relayed to output devices that carry out desired actions such as, controlling wheelchair, or turning on a TV as presented in Fig. 1. BCI is being examined as a rehabilitation device to help people re-gain motor skills that are lost (e.g. from stroke) as well as a prosthetic device to replace or compensate for motor skills that will never return. Fig. 1 illustrates that BCIs convert human intentions or thoughts into control signals to establish a direct communication channel between the human brain and output devices. As can be seen in Fig. 1, the input to a BCI system is the brain signals which are being referred to as Electroencephalogram (EEG) signals. EEG is the measurement of electrical signals from the scalp that result from the neuronal activity of the brain [4]. In the BCI system, EEG is the most widely used measure of potential, mainly due to its excellent temporal resolution, non-invasiveness, usability, and low set-up costs [24,38].

The motor imagery (MI) based BCI is capable of translating the Subject's movement intention to controls the external devices [5, 23]. Imagining a movement or performing an action mentally is known as MI. In MI tasks, Subjects are instructed to imagine themselves performing a specific motor action (e.g. hand, foot) without overt motor output and each task is treated as a MI class [6,23]. In the BCI development, users produce EEG signals of different brain activity for different MI tasks that will be identified by a system and are then translated into commands [25,37]. These commands will be used as feedback for motor disabled patients to communicate with the external environments as illustrated in Fig. 1. If MI is reliably distinguished by recognizing patterns in EEGs, then motor disabled people could control a device by composing sequences of mental tasks [4]. Thus, a MI-based BCI provides a promising control and communication means to people suffering from motor disabilities.

BCI can be designed in two ways: Subject-dependent (SD) based BCI and Subject-independent based BCI. In the SD based BCI, the training part in the MI classification requires a significant number of EEG signal features for recognizing MI patterns of a specific Subject with an acceptable performance [27]. The SD based BCI system requires long recording sessions and afterwards several training sessions for the Subject to be able to use the system [7]. But, most of the case, it is difficult for some patients, (e.g. stroke patients) who do not have the physical or mental availability to complete long trials required for the SD based BCI implementation. To solve these problems, the SI based BCI is introduced that enables a new user to achieve good performance with minimal training that can decrease the tiresome sessions [26]. In the SI based BCI, the systems are trained with the data of a group of Subjects instead of a single Subject. Therefore, SI based BCI is more effective for the patients with neuro motor disabilities as most of the patients do not have the physical capability to train the system. Thus this study intends to develop method for classification of MI task for SI based BCI system.

Most of the research works in the BCI field has focused on the SD based BCIs while there are very few on the SI based BCI although it has more benefit. Lotte et al. [8] explored the design of a SI BASED BCI system with Filter Bank Common Spatial Patterns (FSCSP). They compared different features and classifiers on data from nine Subjects. Fazli et al. [9] reported a design of a SI based BCI with an ensemble of classifiers derived from spatial and temporal filters specific for each Subject was presented. Blankert et al. and Krauledat et al. [10,11] studied to develop ready-to-use BCIs for unknown Subjects. Their methods are only applicable for one or two unknown Subjects whereas the main target of ready-to-use BCI is to design a tool for all untrained subjects.

This work explores the design of a SI based BCI in the classification of mental states based on MI task. In the proposed method, in order to remove noise from EEG data, we employ fifth order Butterworth filter and then use common spatial pattern (CSP) to find prototypical spatial filters from past sessions of a specific Subject. In the feature extraction part, we use four feature extraction methods such as, Katz Fractal Dimension, Sub band Energy, Log Variance and Root Mean Square (RMS) to investigate their effectives. We have selected four feature extraction methods among them two methods based on time domain (Katz Fractal Dimension and Log Variance) and the other two methods (Sub Band Energy and RMS) extract features using wavelet decomposed signals. As EEG signals are non-stationary, traditional frequency analysis based feature extraction methods such as FFT only contains the frequency information. It does not contain any time domain information. However, time domain information is very important to enhance the classification result. Again wavelet domain features contain both time and frequency domain information at the same time. That is why in this research we have employed both time and wavelet features. According to our knowledge no previous researcher used both time and wavelet domain features in the case of Subject independent research. We applied both time and frequency domain information for the classification of Subject independent based BCI. In this work, the system is trained by using the data from multiple Subjects and tested it on untrained Subject's data. Linear Discriminant Analysis (LDA) is considered for solving the classification problem as it is very popular in the MI based BCI applications. Out of these four feature extraction methods, in most of the cases, Katz Fractal Dimension method yields better performance with the LDA classifier [28]. In this study, we examine the performance of the proposed design in several ways such as, based on time window, based on frequency bands, based on the number of channels and several designs using different features. The proposed approach is evaluated on dataset, IVa of BCI Competition III [12,13], which contain MI EEG recorded data. A 10-fold cross validation method is applied to assess the performance of the proposed method and also to control over-fitting of the data.

2. Methods

The current study is aimed to design an efficient SI based BCI tool for classifying MI based EEG signals for the application in BCI systems that can work in automatic way. Fig. 2 shows the different steps of the proposed SI based BCI design. The developed scheme is labeled mainly in four stages: filtering; spatial filtering by Common Spatial Pattern (CSP); Feature extraction and classification as provided in the below sections.

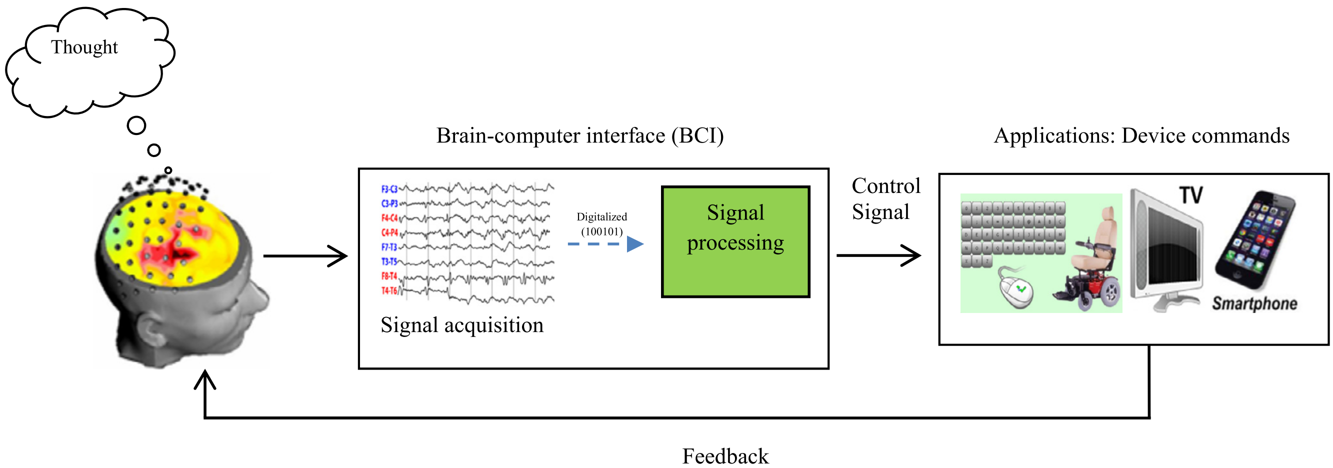

Fig. 1. A fundamental structure of a BCI system.

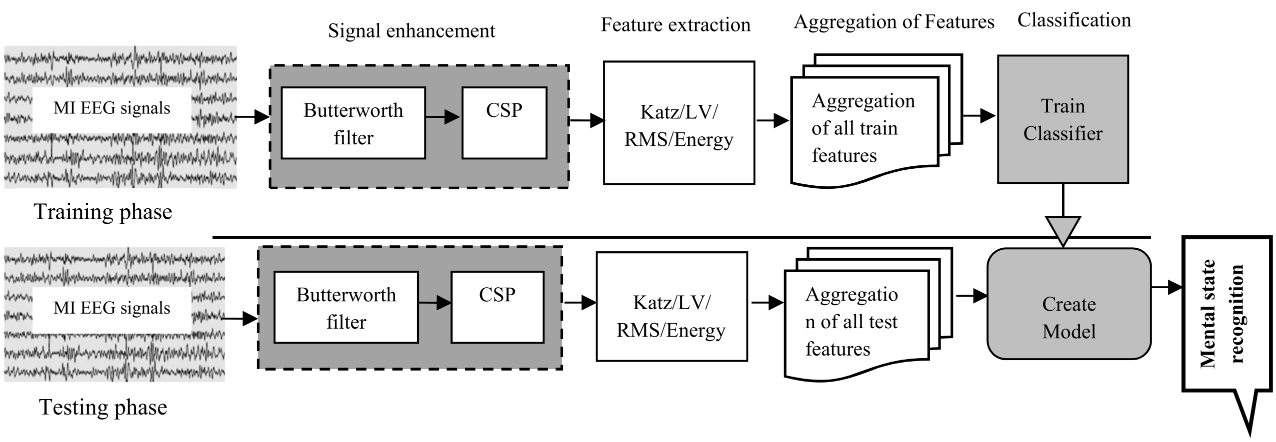

Fig. 2. An outline of the proposed subject independent based BCI system for mental state recognition.

2.1. Filtering using Butterworth filter

A big challenge is for BCI systems to correctly and efficiently identify different MI based EEG signals as EEG data are naturally non-stationary, highly noisy and contaminated with artifacts [3,14]. As EEG signals are affected by noise, it is very important to remove noise from the original signal. As alpha (8-12 Hz) and beta band (12-30 Hz) contains more relevant information for motor imagery tasks, that's why, in our proposed design, we consider a fifth order Butterworth filter ranging from 8-30 Hz.

2.2. Spatial filtering using Common Spatial Pattern (CSP)

EEG signals are recorded from multiple electrodes placed in the scalp of a subject. These multichannel EEG signals have very low signal-to-noise ratio (SNR) [29]. That is why spatial filtering is necessary to enhance the SNR. One of the most effective methods in this field is Common Spatial Pattern (CSP). The use of Common Spatial Pattern is very high for designing a BCI tool as it differentiates the variance of EEG signal from one class to the other. The target EEG potentials tent to have very poor resolution in the specific frequency range [15]. CSP is a supervised decomposition of original signals constrained by a projection matrix $W\Re^{Ch\times Ch}$ where Ch symbolizes the number of channels. W projects the single trial EEG signal $E \in \Re^{Ch\times T}$, which is seen in the sensor space, as follows:

$$P = W \times E \tag{1}$$

where E is $Ch \times T$ EEG measurement of a single trial, and T is the number of time points per channel. W is desired matrix, its rows are the spatial filters and columns are the common spatial patterns. Fig. 3 displays an exemplary pattern of the output Signal of CSP for all the Subjects.

2.3. Feature extraction

Choosing good discriminating features is the key to any successful pattern recognition system [22]. It is usually hard for a BCI system to extract a suitable feature set which distills the required inter-class discrimination information in a manner that is robust to various contaminants and distortions [4]. This study investigates to have an optimum approach for feature extraction from MI based EEG signals which can effectively represent of the original EEG recordings. The extracted features provide the inter-class discrimination information for detecting different categories or different classes (e.g. right hand movement; right foot movement) of MI tasks. To extract the discriminative information from MI based EEG signals it is very important to use the suitable feature extraction methods. In some cases, time domain provides better result whereas in some other cases wavelet features performs well. In our proposed design we have applied both time and wavelet features to obtain their performance. In this study, we consider four efficient and popular methods such as Katz Fractal Dimension,

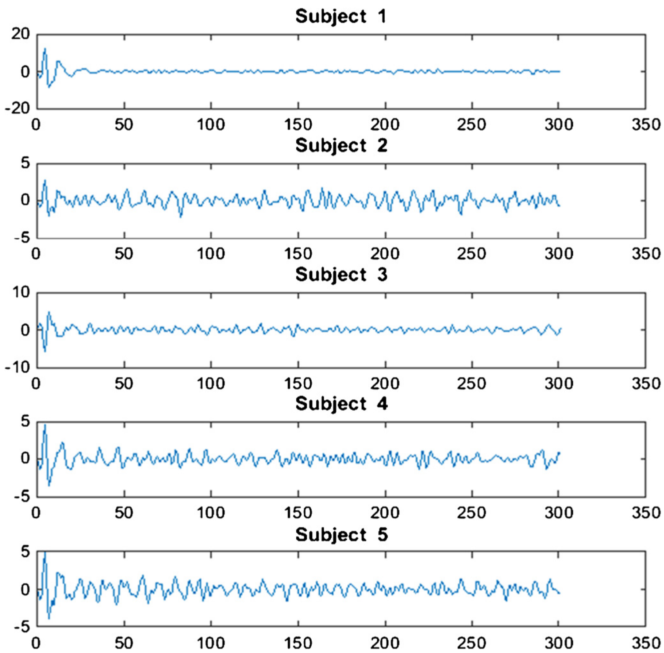

Fig. 3. An illustration of the output signal of CSP for all the Subjects.

Energy, Log Variance and Root Mean Square (RMS) for obtaining discriminative features from MI EEG data. Fractal dimension indicates the degree of roughness or irregularity of a signal. There are several methods for calculating the fractal dimension such as: Katz, Higuchi, and Peterson [33]. Among them the Katz method is more robust for BCI application [34] and that is why this method has been implemented in this research. Until now, there are several feature extraction methods have been proposed and CSP based log variance feature is most popular among them for the classification of MI signal [35]. The CSP method initially seeks spatial filters to project EEG signal onto to a space where the variance of the projected signal of a class is maximized while the other one is minimized. Thus, CSP method is applied on bandpass filtered signal to efficiently extract the discriminative information of MI task. Another popular feature extraction method for MI signal is Fast Fourier Transform (FFT), but there is a limitation for this method is that it only contains the frequency information. The FFT method cannot capture the time information [36]. To overcome this limitation researchers have proposed wavelet transform method which contains both time and frequency information. The wavelet method basically splits the original EEG signa into two subspaces. Complementary to each other, one subspace captures the low frequency information whereas the other one contains the high frequency information. Among all the features two feature sets have been extracted using time domain signal directly such as CSP based Log Variance and Katz Fractal Dimension, the other two feature sets have been extracted from wavelet decomposed signal such as RMS and Sub Band Energy. In this research we compared all types of feature extraction methods i.e. time domain, wavelet based feature and Fractal dimension feature. Brief descriptions of those methods are provided below.

2.4. Katz fractal dimension

This method actually calculates the degree of irregularity of a signal. The Euclidean distance of the sum (L) and average (a) are calculated between the points of the sample [16]. It also calculated the distance between the initial point and any other point of the sample. The fractal dimension (D) can be calculated by the equation:

$$D = \frac{\log(L/a)}{\log(d/a)} = \frac{\log(n)}{\log(n) + \log(d/L)} \tag{2}$$

where $n = L/a$. This method was proposed by Katz et al. [16].

2.5. Log Variance (LV)

This feature is calculated by measuring the variances of the spatially filtered EEG signals. The feature set contains the variances of the signal z. These variances are finally normalized by the total variances of the projections and are log transformed. The mathematical formula to calculate LV is given below which is used in [31]

$$f_p^i = \log\left(\frac{\mathrm{var}(z_p^i)}{\sum_{p=1}^{2m} \mathrm{var}(z_p^i)}\right) \tag{3}$$

2.6. Wavelet based sub-band energy

Sub-band energy of different wavelet decomposition levels is calculated as feature [30]. The mathematical formula for calculating the energy is given below:

$$E_n = \sum_{m=1}^{M} |T_{nm}|^2 \tag{4}$$

The above equation shows the energy of decomposition level n, where $n = 1 \ldots N$ are the decomposition levels, which is a sum of square of wavelet coefficients T (M is the number of coefficients at each level).

2.7. Wavelet based root mean square

This feature is also calculated from the different levels of wavelet decomposed signals. The formula for calculating the feature is given below:

$$RMS_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N} D_i(n)^2} \tag{5}$$

2.8. Mental state recognition

This study employs Linear Discriminant Analysis (LDA) method on the obtained feature set to detect two-class mental imagery tasks for the application of BCI systems as this classifier can perform very well without high computational cost and very popular for solving the classification problem in the field of BCI. Several researchers have used this classifier in the case of designing BCI system [17–19]. This classifier is used frequently in the case of binary classification. For a binary problem, LDA assumes that the classes are linearly separable [32]. Based on this assumption, LDA generates a linear discrimination function which characterizes a hyper plane in the feature space in order to identify the classes. In the case of multiclass where $N > 2$, several hyper planes are used.

LDA initially maps the feature vector x to be classified by the equation given below:

$$y = w^T x + w_0, \tag{6}$$

where w and w_0 are determined by maximizing the ration of between-class variance to within-class variance to guarantee maximal separability [20]. The within class variance matrix can be defined by

$$S_W = \sum_{i=1}^{k}\sum_{i=1}^{L_i}(x^i - \mu_i)(x^l - \mu_i)^T, \tag{7}$$

where k is the number of classes, and μ_i the mean vector of the class I, L_i the number of samples within class i, and the between-class variance matrix is defined by

$$S_b = \sum_{i=1}^{k}(\mu_i - \mu)(\mu_i - \mu)^T, \tag{8}$$

where μ is the mean of the entire training sample set.

The classification is conducted as follows (a two class problem is used as example):

$$x \in \left\{ \begin{matrix} class\ 1, & if\ y > 0, \\ class\ 2, & if\ y < 0. \end{matrix} \right\} \tag{9}$$

3. Results

This section presents the experimental results of the proposed SI based BCI design for dataset, IVa of BCI Competition III [13]. The data was recorded from 5 healthy Subjects performing right hand foot MI tasks. Subjects were sitting on a comfortable chair with arm resting on armrests when recording the data. The EEG signals were recorded using 118 channels at a sampling frequency of 1 KHz. A single trial consists of a total 280 MI tasks among then 140 for each MI tasks for each Subject. The duration of a single trial was 3.5 second.

In the experiment, we used the individual classification of the trials, i.e., we assigned a class to each trial. We extracted features using the data of 2.5 sec instead of 3.5 sec. We considered the data after 0.5 sec of the visual cue. Then a 5th order Butterworth filter was used as band pass filter. The frequency range of the filter was 8-30 Hz. For spatial filtering, a Common Spatial Pattern (CSP) was used. In this work we used all the 118 channels as input and 4 pairs of filters were selected as output. As we know Subject independent experiment is not similar to the Subject dependent MI tasks classification experiment. In the case of Subject independent system, there is no information of test signal in the training phase of classifier. In our experiment, we considered the data from 5 individual Subjects. We used the data of 4 Subjects for training the classifier and the data of rest one Subject have been used as test data. Then we have cross-validated the data by rotating the test data.

As classification accuracy is considered as a major issue in BCI systems, this study considers classification accuracy for performance evaluation and also uses sensitivity and specificity. The mathematical formula to calculate the accuracy is given below:

$$Classification\ accuracy = \frac{Correctly\ classified\ test\ trials}{Total\ test\ trials} \times 100$$

$$Sensitivity = \left(\frac{True\ positive}{True\ positive + false\ negative}\right) \times 100$$

$$Specificity = \left(\frac{True\ negative}{False\ positive + True\ negative}\right) \times 100$$

In this paper, we used MATLAB software package (version 7.14, R2012a) for all mathematical calculations.

Table 1 presents the comparative results of different features in the classification of the MI based mental state tasks for SI based BCI systems. In this table, the performances for both time domain and wavelet based feature are provided in terms of Subject-specific accuracy, and overall accuracy, sensitivity and specificity. As can be seen from Table 1, Katz fractal dimension feature yields better performances in most of the cases of Subject-specific, (e.g. for Subjects 1, 3 and 4) and also in overall while Log Variance feature generates better results only for Subject-2 and the wavelet based RMS feature only for Subject-5. It means Katz feature contains important information for classifying MI based mental states in EEG for SI based BCIs.

Table 1
Classification results for different features using whole channel data (118 channels).

Individual subject-accuracy	Features			
	Katz	Energy	LV	RMS
Sub-1	86.78	50.71	82.85	70.35
Sub-2	90.35	63.57	95.0	92.85
Sub-3	68.92	54.28	61.42	57.5
Sub-4	92.14	62.81	79.28	83.21
Sub-5	83.57	37.85	81.78	91.78
Overall performances				
Accuracy	84.35	53.85	80.06	79.14
Sensitivity	81.28	33.42	81.85	68.14
Specificity	87.42	74.28	78.28	90.14

Note: Sub-1= Subject 1; Sub-2= Subject 2; Sub-3= Subject 3; Sub-4= Subject 4; Sub-5= Subject 5.

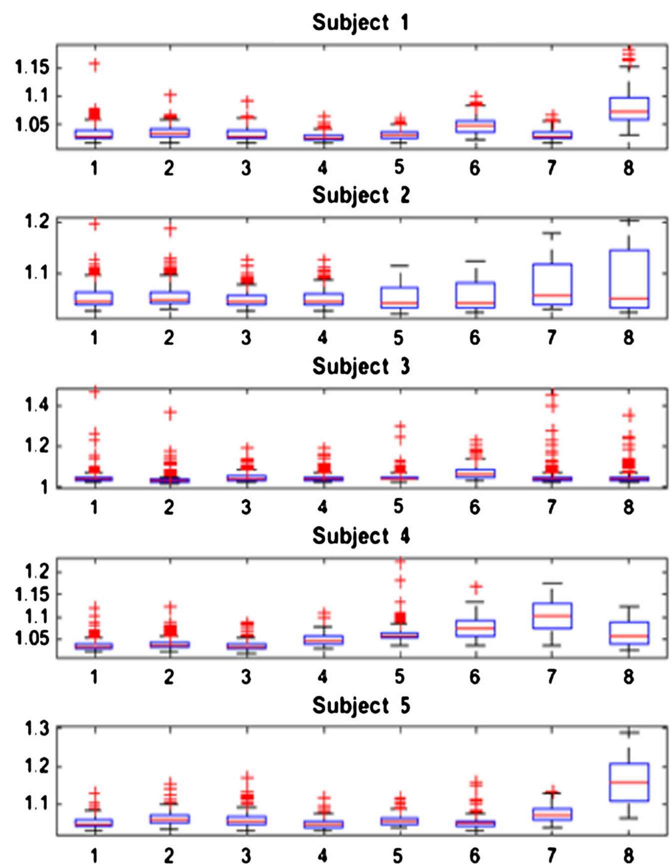

Fig. 4. An illustration of Katz fractal dimension feature by box plot.

By analyzing the above table, it can be said that time domain based Katz fractal dimension feature carries important information for most of the Subjects. Considering the Subject-specific results and also overall results, it can be said that Katz fractal dimension has more capability to produce better performance in the SI based MI task classification. Hence, in this study we consider this feature for our further experiment evaluation. Fig. 4 displays an example of the distribution pattern of Katz fractal dimension feature in terms of channels for each individual subjects by box plots. It can be seen, in X axis, the number of channels are putted and Y axis shows the magnitude of Katz feature. As we can see from Fig. 4, in most of the cases, the distribution of Katz feature in individual

Table 2
Classification performance for different frequency bands using Katz fractal dimension feature.

Ind. sub.-acc.	Frequency band				
	0.1-4 Hz	4-8 Hz	8-12 Hz	12-30 Hz	8-30 Hz
Sub-1	89.64	83.21	51.07	86.78	86.78
Sub-2	90.00	81.42	97.50	90.35	90.35
Sub-3	85.35	82.50	76.42	68.92	68.92
Sub-4	88.57	80.35	93.92	92.14	92.14
Sub-5	85.35	76.78	96.78	83.57	92.14
Overall performances					
Acc.	87.78	80.85	83.13	77.35	84.35
Sen.	88.85	87.14	70.14	75.85	81.28
Spe.	86.71	74.56	96.14	78.85	87.42

Note: Acc. = Accuracy; Sen = Sensitivity; Spe. = Specificity; Ind. sub-acc. = Individual Subject Accuracy.

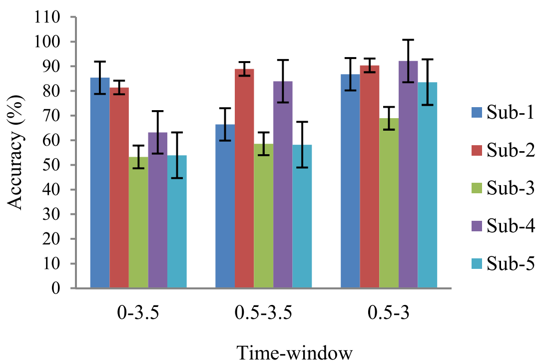

Fig. 5. Classification performance for different time-window length. Error bars indicates the standard error.

channel are not similar which in refers to that Katz feature convey more discriminating information for better classification.

Table 2 shows the performance of different frequency bands using CSP spatial filter with Katz fractal dimension feature. By analyzing the above table, it can be said that the information required classifying the MI data lies in some specific frequency bands. Subject-1 and Subject-3 provides performs best in frequency range 0.1-4 Hz. The classification accuracy of these two Subjects in this band is 89.6 and 85.35% respectively. Rest of the Subjects shows their best performance in the frequency 8-12 Hz. The results obtained in this frequency band for Subject 2, 4 and 5 are 97.5, 93.92 and 96.78% respectively. IF we consider a very wide frequency range e.g. 8-30 Hz the mean classification result decreases in comparison to the mean result of low frequency bands. The value of sensitivity and specificity is very maximum for frequency range 0.1-4 Hz and 8-12 Hz respectively.

Fig. 5 shows the comparative result of different size of window. The classification accuracy is very low when we consider the window size very large e.g. 3.5 s. It indicates that the whole data does not contain important information rather it provides unnecessary information which affect the mean classification. A very interesting finding from the above table is that decreasing of window size increases the classification accuracy. The classification accuracy is 71.2% for considering the window size 3 s (0.5-3.5). However, this result also improves significantly when we decrease the window size more. The maximum classification accuracy is obtained for selecting the window size 2.5 s which is 84.35%. SO, it is very important to select the window size wisely. Vertical lines on the top of the bar charts show standard error of the three time-window length. Lower standard error indicates more reliability.

Table 3 presets the classification results for the different number of channels in the MI task classification for SI based BCI systems. We have examined the classification performance based on

Table 3
Classification performance for the different number of channels.

Individual subject-accuracy	Number of channels		
	3	18	118
Sub-1	50	73.57	86.78
Sub-2	87.5	55.71	90.35
Sub-3	57.85	71.07	68.92
Sub-4	64.28	87.14	92.14
Sub-5	50	55.71	83.57
Overall performances			
Accuracy	67.92	68.64	84.35
Sensitivity	62.14	67.56	81.2
Specificity	61.71	69.71	87.42

the channels from only motor cortex region, motor cortex and surrounding region and the whole brain. That is why we have selected these 3 types of channel setup. In the first case, 3 channels are selected from motor cortex region, in the second case channels are selected from the surrounding of motor cortex region and finally the 118 channels are used from the whole brain. Most of the Subjects provide their best results for considering all the channels. Only Subject-3 performs better when we consider 18 channels. The maximum classification accuracy of this Subject is 71.7% for considering 18 channels. In the case of channel number 3 Subject-2 provides best result among all the Subjects. For the case of 18 channels Subject is the best performer. Finally, for the case of 118 channels Subject-4 provides its best result. The pattern of the results of the above table indicates that by increasing the number of channels always includes important information considering the mean result. The value of sensitivity and specificity is also maximum for selecting the channel number 118.

Maximum value of true positive and minimum value of false positive rate of a ROC curve is expected from a designed method. Fig. 6 (a)-(e) presents the ROC curves for all subjects using Katz feature. In our designed method it is observed that the true positive rate is very high for Subject-2 and 4, which indicates that our designed tool can identify the MI tasks of these two subjects very accurately. The value of true positive rate is very low for Subject-3 among all the Subjects. The true positive rate of Subject-3 and 5 is similar which is higher than Subject-3 and lower that Subject-2 and 4.

4. Discussion

In this research, we have explored a design of mental state classification for SI based BCI systems. The proposed design uses several feature extraction methods including Katz Fractal Dimension, Sub band Energy, Log Variance and Root Mean Square (RMS) with LDA classifier on MI based EEG data. The method is tested on data set Iva of BCI competition III. The performance of the proposed design is evaluated in several ways such as, based different features; based on time window; based on frequency bands; based on the different number of channels. The experimental results demonstrate that Katz Fractal Dimension feature is the best choice to classify the SI based MI EEG signals. The results also reveal that decreasing of window size increases the classification accuracy and the maximum classification accuracy is obtained for the window size 2.5 s. Another finding is that most of the subjects show their best performance in the frequency 8-12 Hz. The reason may, alpha (8-12 Hz) band contains more relevant information for motor imagery tasks. The results also show that most of the Subjects provide their best results for considering all the channels data instead of motor cortex region channels (3 channels) and the surrounding of motor cortex region channels (18 channels). Thus, these results suggest the possibility of designing SI based BCI based on MI.

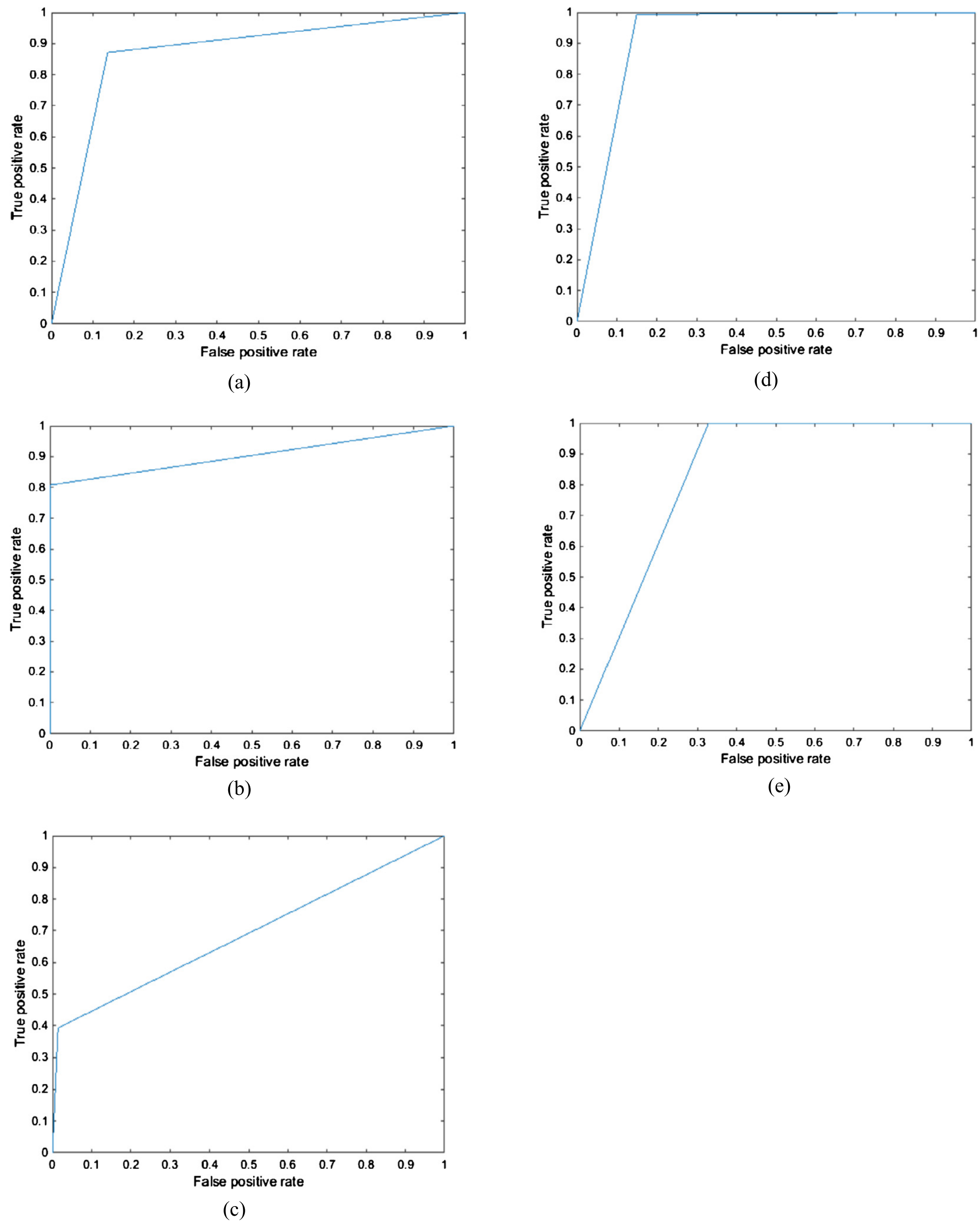

Fig. 6. ROC curves of all five Subjects for proposed methods based on Katz feature: (a) for Subject-1, (b) for Subject-2, (c) for Subject-3, (d) for Subject-4 and (e) for Subject-5.

Table 4 shows the comparative results of our proposed method with the existing methods. We did not get any research in SI-based MI signal classification using the data set we have used this experiment. So we have compared our result with the results in the literature used different data set. Lotte et al. [8] compared the design of subject independent BCI based on MI signal using the data of BCI competition IV data 2a. They reported maximum classification accuracy 70.99% using LDA classifier for SI-BCI. Negrete et al. [7] proposed an approach to improve the performance of SI-BCI based on MI signal allocating subjects by gender. In their experiment they collected the data from 32 healthy subjects among them 50% male and 50% female. They got the maximum classification accuracy for female patient in the case of Right hand vs. Rest which is 83%. In this experiment they used log variance as feature. Reuderink et al. [21] proposed a SI-BCI based on Smoothed, Second-Order Base lining using the data from 109 subjects. The data set contains both actual and imagined movement of feet and hand. They reported maximum mean classification accuracy 67.3%. Using our proposed method, we got mean classification accuracy of 84.35% using the data from 118 channels.

5. Conclusions

This paper presents a novel idea to classify mental states for SI based BCI system. The proposed method employs four types of feature extraction methods including Katz Fractal Dimension, Sub band Energy, Log Variance and Root Mean Square (RMS) for extracting representative features from brain signals and finally those features are used in Linear Discriminant Analysis (LDA) classification model for classifying mental states in SI BCI system. The proposed scheme is tested on data set IVa of BCI competition III. All experiments are evaluated through a 10-fold cross-validation

Table 4
Comparison of the classification performance between our proposed algorithm and the most recent reported algorithms for SI-BCI.

Authors	Methods	Accuracy
Lotte et al. [8]	LDA with 20 pairs of features using MR FBCSP	70.99%
Negrete et al. [7]	CSP-Log Variance and LDA classifier	83%
Reuderink et al. [21]	Second Order Baselining (SOB) with LDA and SVM	67.3%
Proposed method	CSP and Katz Fractal Dimension feature with LDA Classifier	84.35%

process, which indicates the reliability of the obtained results. The performance of the proposed design is evaluated in a number of ways such as considering different time window length; different frequency bands; different number of channels. The results show that the CSP and Katz Fractal Dimension feature with the LDA classifier achieves a better performance compared to the other features in IVa dataset. This study concludes that the CSP and Katz feature based LDA algorithm is a promising technique for mental state recognition in Subject Independent BCI Systems and it offers great potentials for the development of mental state based BCI analyses which assist clinical diagnoses and rehabilitation tasks.

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Author contributions

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

Declaration of Competing Interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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