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A Review on EEG Classification for Motor Imagery Brain Computer Interface

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Abstract: Brain Computer Interface (BCI) is a communication pathway between a human brain and an external device. For paralysed people BCI acts as an interface to control and regulate external devices and replaces their lost motor functionality. A motor imagery BCI converts a subject's thought about a motor activity into control signals which in turn controls the intended device. The EEG signals that are produced according to the motor imaging need to be processed and analysed using various signal processing algorithms. Learning and modelling the brain activity presents a huge challenge in the accurate classification of this EEG and hence affects the performance of the BCI system. The importance of feature extraction stage is that, since the brain regions work in collaboration during an activity the correlation between the EEG signals must be considered during this phase. The tasks need to be classified accurately by efficient feature translation algorithms. This paper is a study on different signal processing techniques for the accurate extraction of EEG features and their classification for an efficient motor imagery BCI system. Different discrimination algorithms based on frequency, temporal and spatial domains are being analysed.

Keywords: Brain Computer Interface, Linear Discriminant Analysis, Separable Common Spatio –Spectral Patterns, Neural Networks, Common Bayesian Network.

I. INTRODUCTION

Brain Computer Interface is a technology that has seen rapid growth in the recent years. For people who are fully or partially paralysed or who are suffering from disorders like amyotrophic lateral sclerosis, BCI can act as an interface between the users and an external device. It is a communication pathway between an enhanced human brain [2] and the device. It controls the mechanical or electronic devices based on the brain activity alone. For such people who are paralysed, their brain regions might be working well. So the users can imagine the movement of their body parts and corresponding brain signals will be produced. BCI decodes these signals can interface them to the intended device. It actually restores the movement ability of paralysed users and the lost motor functionality is being replaced. Other than the biomedical applications, BCI becomes useful in places where the response time is crucial. It has a wide variety of applications [5] in the fields of neuro-ergonomics, neuro-marketing, educational self regulation, games, entertainment and security.

EEG based motor imagery BCI systems are the most studied form of BCI. Motor Imagery refers to the imagination of movement of body parts. When a movement is being imagined, corresponding brain regions will be activated and the EEG signals will be produced according to the imagined movement. It is the motor areas of the brain that gets activated during the imagination of a motion. The motor imagery modulates the sensorimotor rhythms in the EEG signal. Mu rhythms (8-12 Hz) which is simply the alpha rhythms recorded in the motor areas and the beta rhythms (12-30 Hz) are the sensorimotor rhythms. These variations in the EEG rhythms are analysed and processed in the BCI. The control signals corresponding to these variations are produced and are used to control the intended devices like wheelchair, lamp, robotic arms etc.

The basic structure of BCI includes a source module, a signal processing module and a user application module. The source module carries out the data acquisition and stores the data as such without any processing. In an EEG based system, the data corresponds to the EEG signals acquired in accordance with the imagined movement. In the signal processing module, the pre-processing of the EEG signal is done. The signal is modified to a form in which further processing by removing the artifacts and other noises. The feature extraction and classification is carried out in this module. The accuracy of this module determines the accuracy of the entire system. The user application module is the module which interfaces the processed control signal to the intended device. This module drives the application using the control signals. Since it is important to identify the significant features of EEG during a motion and accurately classify these features, the signal processing module is the most important part of a BCI system. Feature extraction and classification algorithms are hence an integral part in a BCI system. Many researchers are working on the enhancement of these algorithms. Some methods work using the spectral characteristics of the motor imagery EEG signals and some methods work based on the spatial features. Sometimes, combinations of both these are used for the discrimination of

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features which increases the information transfer rate [1]. In this paper we discuss about some efficient feature extraction and classification methods used in EEG based motor imagery BCI. The basic structure of a BCI system is shown in Fig. 1. Different algorithms are being experimented for feature extraction and classification.

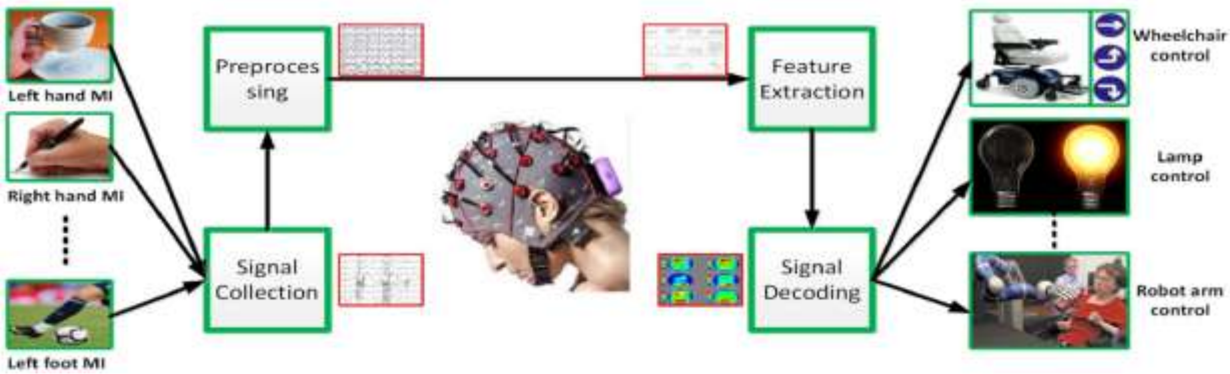

Fig. 1. Basic structure of an EEG based MI BCI system

II. DIFFERENT METHODS FOR FEATURE EXTRACTION AND CLASSIFICATION IN BCI

A. Method using Linear Discriminant Analysis

A classification method for motor imagery tasks in Brain Computer Interface using Linear Discriminant Analysis [4] is proposed by Roxana Aldea and Monica Fira. In this method the motor imagery feature extraction is done using multiresolution wavelet analysis and the task classification is done by using the LDA method. The two classes being classified are the left or right hand imagery movement and rest. The work is done using the EEG data recorded with 8 g.tec active electrodes by means of g.MOBIlab+ module. The paper tries to make a comparison between the LDA classification method using these acquired EEG signals and the LDA classification method used in the BCI2000 [3] systems.

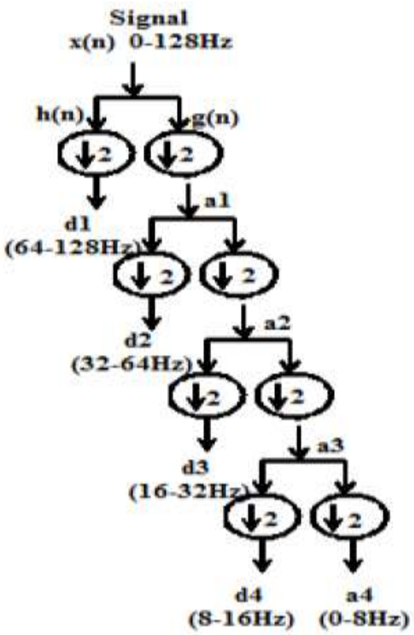

Fig. 2. Schematic of fourth level multiresolution wavelet decomposition

The sensorimotor rhythms, which are the mu (8-12 Hz) and beta (12-30 Hz) rhythms, are extracted using wavelet decomposition. Since the EEG data acquired is in the range 0-128 Hz, fourth level multiresolution wavelet decomposition is done using Coiflet4 wavelet, to obtain the mu and beta rhythms. The schematic of fourth level multiresolution wavelet decomposition is shown in Fig. 2. The multiresolution wavelet analysis provides localization in both time and frequency domain. CP3, CP4, P3, Cz, Pz, C4, P4 and Cz are the channels where the electrodes are placed due to the presence of sensorimotor rhythms in these areas. The detailed coefficient of fourth level decomposition and

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the detailed coefficient of third level decomposition are then classified using the LDA classifier. A discriminant vector that separates the classes best possible is computed in this method. The basic principle of LDA is that for each identified class, a linear function of attributes is computed and the predicted class is represented by the class function with the highest score. The advantage of using LDA is that, for the optimization purpose, it does not require multiple passes over the data. Since it can obtain probability estimation for each class, it can also deal with problems where there is more than two classes.

B. Method using Fuzzy System

In the method proposed by Thanh Nguyen, Saeid Nahavandi, Abbas Khosravi, Douglas Creighton and Imali Hettiarachchi, the EEG analysis for BCI is done based on Wavelet Transform and Fuzzy Standard Additive Model (FSAM) [6]. Wavelet transform decomposition using fourth level Haar wavelet is used for extracting the required features. Due to the compact support and orthogonality features of Haar wavelet, it is more suitable in characterizing the features of EEG samples by a few representative wavelet coefficients. Once the decomposition is done, the significant wavelet coefficients need to be selected. For this, Wilcoxon rank sum test is employed in this work. This is a nonparametric test and it evaluates the quality of population locations which is based on the medians. The method first sorts the observations of the two-class populations in ascending order. The sum of all the ranks corresponding to the observations from the smaller group gives the Wilcoxon statistic and the hypothesis decision is made based on these statistics. Since Haar wavelet is orthogonal, the coefficients with higher rank are considered to be more prominent.

The feature set obtained as a result of Wilcoxon test is a combination of the selected coefficients. FSAM is employed for the classification purpose. The learning process in FSAM comprises of unsupervised and supervised learning steps. For unsupervised learning steps. For unsupervised learning, Tabu search algorithm is used which constructs the if-then fuzzy rule structure. In order to tune the rule parameters, supervised learning is carried out. Number of inputs to the FSAM system is determined by the number of features in the training feature set. The hypothesis is modelled to be Gaussian fuzzy sets and the centres of these sets are made equivalent to the feature values. These centres are then assigned the values ‘1’ or ‘2’ which represents the samples for class ‘1’ or ‘2’. Before processing, the raw EEG signal data are divided into separate channels and wavelet transform is applied separately in each channel to obtain the information in the EEG. Using a fuzzy model is advantageous due to the nonlinear and noisy nature of EEG. The schematic of a Tabu FSAM classifier with wavelet features is given in Fig. 3.

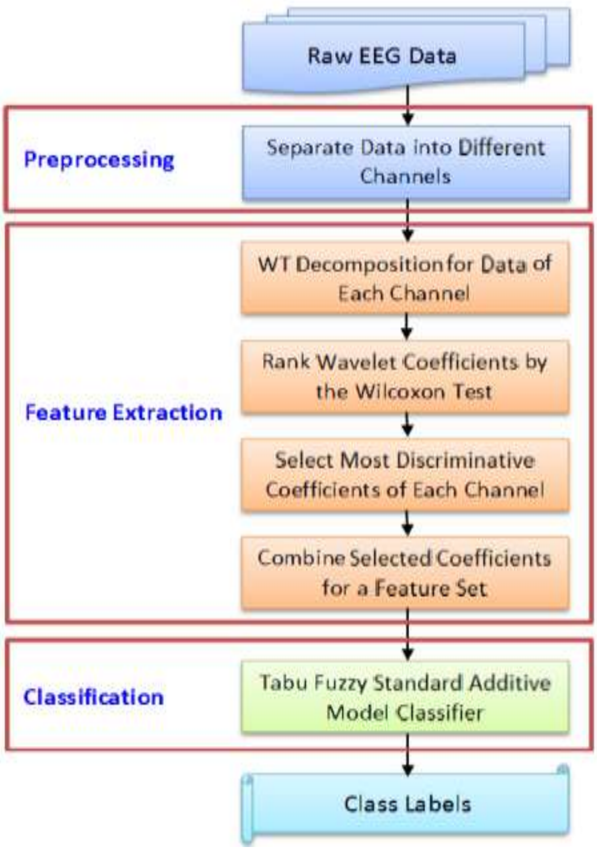

Fig. 3. Schematic of Tabu FSAM classifier with wavelets features.

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C. Method using Separable Common Spatio-Spectral Patterns

Common Spatial Patterns (CSP) is an effective method for the feature extraction in motor imagery BCI systems. An extended form of this is proposed by Amirhossein S. Aghaei, Mohammed Shahin Mahanta and Konstantinos N. Plataniotis, which is the Separable Common Spatio-Spectral Patterns (SCSSP) [7]. CSP analyses the data in spatial domain and the spatial features are extracted for further processing. It does not consider the spectral characteristics of the data. Unlike CSP, SCSSP takes into account both spatial and spectral characteristics of the EEG data. This method jointly processes the EEG in both spatial and spectral domains and this is achieved by using a heteroscedastic multi-variate Gaussian model for the EEG rhythms. The work focuses on binary classification problem but it can be extended to multiclass scenario. The features are extracted in such a way that their variance is maximized for one imaginary motion and is minimized for the other motion.

The paper also gives a comparison between the conventional FBCSP and the proposed SCSSP. Even though FBCSP is a computationally efficient algorithm; it ignores the spectral features of the signal and does not consider the correlation between the EEG rhythms. This problem is being rectified by the SCSSP method. SCSSP also ranks the discriminant features and helps in dimensionality reduction which further eliminates the need for a separate feature selector. It is a bilinear feature extractor and only two CSP modules need to be trained in this. The multiclass extension of SCSSP method can be done using one-versus-rest strategy.

D. Method using Neural Networks

Most of the BCI systems developed are subject specific systems. The system will be trained for a specific user and take inputs from that specific user only. When a new user needs to access such a system, it needs to be trained again for the new user. A multiuser EEG classification method for BCI is being proposed by Sylvia Bhattacharya, Rami J. Haddad and Mohammad Ahad. The method uses a network of artificial neural networks [8] for the classification of different imaginary motions. Raw EEG potentials and pre-computed power Spectral Density are used to train the neural network system using scaled conjugate gradient backpropagation algorithm. A majority vote is used to optimally classify the tasks imagined by multiple subjects. Raw EEG data from three subjects were collected for three different imaginary tasks. Each subject carried out three trials. In order to optimise the classification accuracy, for three users as a group, an optimized set of electrodes were used. For multiuser classification, the channels are ranked based on their individual classification accuracy and then optimized by elimination method. The schematic of majority vote system for ANN is given in Fig. 4.

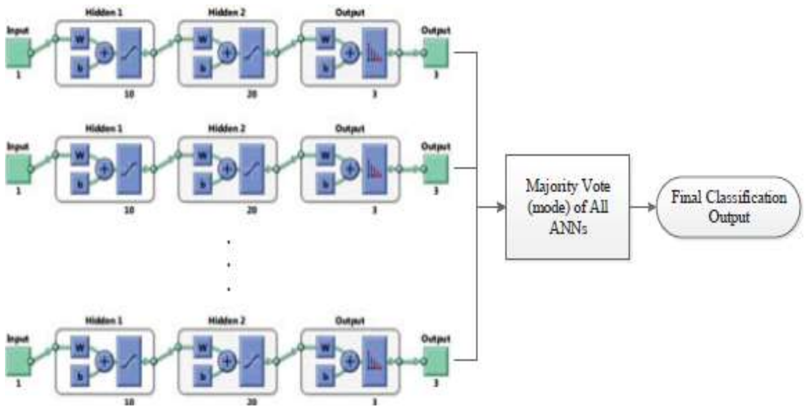

Fig. 4. Majority vote system for a network of ANN

The system uses a three-layer feed forward neural network per electrode. The activation function used is sigmoid function and it contains the hidden and output neurons. In order to improve the reliability of the system, a cross validation method is employed. The paper also gives an account of taxonomy of imaginary motions. It also gives a briefing about the different classifiers used for imaginary motion classification.

E. Method using Common Bayesian Network

Lianghua He, Die Hu, Meng Wan, Ying Wen, Karen M. Von Deneen and MengChu Zhou proposed a method for multiclass motor imagery feature extraction in BCI systems using Common Bayesian Network (CBN). CBN [9] analyses not just the spatial or spectral characteristics, but it takes into account the correlation between different brain regions during an imaginary motion. When a motion is imagined the brain regions work in collaboration. A motion affects not a single electrode (EEG channel) or a set of electrodes but many electrodes get involved in the action. So it is essential to consider the relation between these different electrodes. For this, a Common Bayesian Network is used. CBN discriminates multiclass EEG signals for motor imagery BCI system.

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In this method the first step is to construct a normal Bayesian Network by selecting the related channels. BN is considered to be a directed acyclic graph. The learning task involves the structure learning and parameter estimation steps. A Gaussian Mixture Model is used for structure learning and the conditional probability distributions between these electrodes during activation. By analysing the BN, common edges and key nodes are identified. These nodes and edges are used to construct the CBN. By this method, the error occurred during different trials of imagining a motion is eliminated. The feature vector includes the conditional probability of the common edges in BN. The features extracted via CBN are classified using Support Vector Machine classifier.
The proposed work classifies four motor imagery classes. They are the movement of left hand, right hand, tongue and foot. The method analyses the relationship between the motor areas activated during a task and the motor imagery tasks performed. Since it consider this relationship the system is highly efficient.

III.RESULT ANALYSIS OF DIFFERENT METHODS

The different methods used for feature extraction and translation in motor imagery BCI uses various measures to evaluate the performance of the proposed systems. Some systems were evaluated based on simple percentage of accuracy. The Linear Discriminant Analysis method classified the features using a normal LDA and also an LDA that uses the normalization of the feature matrix is also implemented. The performance of the proposed method was evaluated using EEG data recorded by using 8 g.tec active electrodes by means of g.MOBIlab+ module. The best classification rate [4] is obtained with the normalized LDA and the rate is 86%. TABLE I shows the classification rates for different subjects. It is seen that better classification rates were obtained by using the proposed LDA method than the LDA used by BCI2000 software, for all the subjects.

TABLE I CLASSIFICATION RATES FOR THE MOTOR IMAGERY OF RIGHT HAND SIGNALS VERSUS REST SIGNALS

Sub.	LDA BCI 2000	C3		CP3		P3	
		LDA	*LDA norm*	*LDA*	*LDA norm*	*LDA*	*LDA norm*
1	45%	55%	**73%**	73%	**77%**	77%	**82%**
2	77%	68%	**82%**	82%	82%	77%	**82%**
3	72%	**82%**	77%	**82%**	77%	**77%**	68%
4	63%	77 %	77%	77%	**82%**	**82%**	77%
5	72%	72%	72%	73%	73%	73%	73%
6	54%	77%	**82%**	73%	77%	77 %	**82%**
7	77%	77%	77%	82%	82%	82%	**86%**
8	77%	**77%**	72%	68%	**77%**	77%	77%
9	77%	77%	**82%**	68%	**77%**	77%	73%

In the method using FSAM classifier, the metrics used for performance evaluation are accuracy, F1 score statistics (F-measure), Gini coefficient and mutual information [6]. F-measure uses the 'Precision' and 'Recall' of the classification procedure and calculates the evaluating score as the harmonic mean of 'Precision' and 'Recall'. As F-measure increases, the predictive power of the classification method also increases. Gini index is a performance measure based on the area under a receiver operating characteristic curve. Classifier performance is higher when Gini index is high. Mutual Information (MI) between estimated and true labels is calculated by the joint and marginal probability distributions of estimated and true class labels. Experiments are carried out using two benchmark datasets Ia and Ib, from the BCI competition II dataset. By using the Tabu-FSAM classifier in Ia dataset, the F-measure obtained is 90.07, Gini index is 80.40, MI is 53.82 and accuracy is 90.20. The results show that the proposed classification method is dominant over other methods not only in accuracy but in other measures also.

The SCSSP method uses the correct classification rate (CCR) as the performance measure of the overall system. It is the ratio of number of successfully classified samples over the total number of samples. The system compares the performance measures obtained when different combinations of usage of Surface Laplacian (SL) and Channel Selection (CS) [7] methods used in the feature extraction stage along with the proposed SCSSP method. For these studies, Dataset V from BCI competition III and Dataset 2a from BCI competition IV are used. Dataset V from BCI competition III contains EEG of three normal subjects recorded in four sessions. Each session consists of sequential 15 second trials of the three tasks. Dataset 2a from BCI competition IV contains EEG recordings of nine normal subjects recorded in two sessions. Each session consists of six runs, each of which includes 48 trials of length 3 second. TABLE II shows the %CCR for different combinations.

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TABLE II %CCR FOR DIFFERENT ALGORITHMS

Feature Extraction			Classifier	Performance in Test Stage (%CCR)			
Spatial		Spatio-Spectral					
SL	CS			Subj. 1	Subj. 2	Subj. 3	Average
No	No	FBCSP	NBPW	72.51	57.99	42.37	57.62
			Lin	78.25	68.90	47.96	65.03
		SCSSP	NBPW	73.92	60.26	38.49	57.56
			Lin	77.81	65.33	43.87	62.34
	Yes	FBCSP	NBPW	69.91	50.43	44.95	55.10
			Lin	73.05	55.08	51.72	59.95
		SCSSP	NBPW	70.24	47.95	47.31	55.17
			Lin	74.13	49.35	50.00	57.83
Yes	No	FBCSP	NBPW	69.70	59.72	43.98	57.80
			Lin	76.41	67.71	47.10	63.74
		SCSSP	NBPW	73.16	55.83	38.28	55.76
			Lin	76.84	60.15	46.45	61.15
	Yes	FBCSP	NBPW	72.08	50.76	44.52	55.78
			Lin	73.48	54.21	47.53	58.41
		SCSSP	NBPW	70.13	52.38	44.84	55.78
			Lin	73.59	55.72	48.39	59.23

The neural network method uses a majority vote system where each channel is ranked based on their accuracy. Different sets of electrodes were experimented for the optimization [8] of channels. BCI Competition III dataset V is used as the experimental dataset. In this dataset, data of 3 healthy subjects were recorded, in 3 sessions for each of them performing 3 imaginary motion tasks. Each session lasted for 4 minutes with a break of 5-10 minutes in between. The best classification accuracy obtained is 79.96% when using 15 channels for classification. The classification accuracy also varies across different users since it is a multiuser BCI system. TABLE III gives the accuracy of the system for different sets of electrodes.

TABLE III ACCURACY BY ELECTRODE OPTIMIZATION

No. of Channels	Classification Accuracy
17	78.71%
16	79.21%
15	**79.96%**
14	78.91%

The performance measure used in CBN method is the Kappa Coefficient [9]. It is a measure agreement between categorical items. It represents the proportion of agreement that remains after correction for agreement expected by chance. Since it considers the agreement occurring by chance, it is a more reliable measure than simple percent agreement. When its value is between 0.80 and 1.00, it is said that there is very good agreement. The dataset III2a in BCI competition III and dataset 2a in BCI competition IV are used to test the performance. According to the prior analysis and channel distribution of the two BCI datasets, only 15 channels are selected to construct a BN. The performance is evaluated for different imaging time. It is seen that the performance is maximum during 1.2s and 1.4s duration of a total of 3s imaging time. Most of the subjects have highest performance after 0.8s imaging. The paper compares the Kappa coefficient obtained for different subjects in the BCI III III2a dataset when using different methods for feature extraction and classification. TABLE IV shows this comparison of the system performance.

TABLE IV KAPPA COEFFICIENT FOR DIFFERENT METHODS

Methods	kappa coefficient	Subjects		
		K3	K6	L1
CSP + SVM	0.79	0.82	0.76	0.8
CSP+SVM+kNN+LDA	0.69	0.9	0.43	0.71
PCA + ICA + SVM	0.63	0.95	0.41	0.52
CBN+SVM	**0.9**	**0.98**	**0.88**	**0.82**

IV. CONCLUSION

There has been a rapid growth in the development of Brain Computer Interface for biomedical and many other applications. Different feature extraction and feature translation algorithms are being developed for increasing the accuracy of BCI systems. Some of such methods have been analysed in this paper. The method using LDA is useful for two class problems but it has difficulty with classification of more than two classes. In fuzzy classifier, multiple actions cause the classification task to be more complicated. Also the feature extraction method could have been a more efficient one like the wavelet packet transform. In SCSSP method, high noisy patterns are generated for longer trials. The method using neural networks could classify the signals from multiple users. But the quality of EEG signal generated by subjects degraded with time. Among the feature extraction methods, CBN method is found to be more efficient since, unlike other methods, it considers the correlation between different brain regions during the activation of a motor imagery task. It can classify multiclass motor imagery signals and it has reduced complexity. The common limitation of these methods is that the performance is maximized only during specific durations of imaging time. Future research works can be focussed to overcome these limitations.

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