A Review on Motor Imagery Signal Classification for BCI

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Abstract

Brain computer interface (BCI) is an evolving technology from past few years. Scalp recorded electroencephalogram (EEG) based BCI technologies are widely used because of safety, low cost and portability. Millions of people are suffering from stroke worldwide and become disabled. They may lose communication control and fall into the locked in state (LIS) or completely locked in state (CLIS). Motor imagery brain computer interface (MI-BCI) can provide non-muscular channel for communication to those who are suffering from neuronal disorders, only by imagination of different motor tasks e.g. left-right hand and foot movement imagination. EEG signals are time varying, non-stationary random signals which are changes in person to person and occurs at different frequencies. For real time application of such a system efficient classification of motor tasks is required. The biggest challenge in MI-BCI system design is extraction of robust, informative and discriminative features which can be converted into device commands. The main application of MI-BCI is neurorehabilitation and control of wheelchair or robotic limbs. The objective of this paper is to give brief information about different stages of EEG based MI-BCI system. It also includes the review on motor imagery signal classification.

Keywords: Electroencephalogram (EEG), Brain Computer Interface, Motor Imagery BCI, EEG Signal Classification, Motor Imagery Signal Classification for BCI.

1. INTRODUCTION

BCI is a technology which identifies the intension of person through neural activities and translate the electrophysiological signals into device commands. BCI which is based on sensorimotor rhythms (mu-beta rhythms) produces at the motor cortex area is known as MI-BCI. Using MI-BCI one can communicates with external device by the motor action imagination. It provides communication channel for those people who are suffering from neuromuscular diseases like amyotrophic lateral sclerosis (ALS), brainstem stroke and spinal cord injury. Patients with such disease become paralyzed and loses communication with external environment. Person is completely paralyzed but vertical eye movement and preserved consciousness is present then the patient is said to be in locked in state, while in completely locked in state patient also loses the eye movement and preserved consciousness. BCI can be useful for patients in 'locked-in' (LIS) state and 'completely-locked-in' (CLIS) state. BCI is not only for the rehabilitation but also gives a new direction for the human machine interface, thought driven robots, computer games and virtual reality applications [1][2][3][31].

Biological signal represents the activity of brain as status of whole body in terms of electrical signals. Performance of brain computer interface systems depends on the biological signal analysis. Some biological signals are (1) electrocardiogram (ECG), (2) electroencephalogram (EEG), (3) evoked potentials such as visual, auditory, somatosensory, (4) electromyogram (EMG) and (5) phonocardiogram [4]. Human EEG was discovered by the Hans Berger in 1929. EEG based brain computer interface has become more acceptable nowadays because of portability, low cost and easy application. MI-BCI processes EEG signals and uses its features as device commands. According to signal acquisition BCI can be classified into two classes (1) invasive BCI and (2) non-invasive BCI. In *invasive* BCI system micro-electrodes are placed into the skull of human brain by neurosurgery. Types of invasive BCI are local field potentials, single unit activity, multiunit activity and electrocorticography (ECoG) [15]. Signals recorded from invasive implantation are less noisy and better in quality, but this method has many drawbacks such as infection and posterior surgery. Because of this reason non-invasive techniques are widely acceptable and most researches are based on non-invasive one. In *non-invasive* approach brain signals are acquired from scalp (scalp recorded EEG) without any neuronal surgery. Slow cortical potentials (SCP), sensory motor rhythms (SMR) and beta rhythms related with motor, event related potentials, steady state visual or auditory potentials, functional magnetic resonance imaging (fMRI) and near-infrared spectroscopy (NIRS) are the types of non-invasive BCI [2][5].

Stroke is one of the leading cause of disabilities in the world. Patients may lose their motor control due to stroke. To restore their motor functions MI-BCI is a promising tool. Numbers of research papers are available on motor imagery based brain computer interface for classification of motor imagery (MI) tasks. It shows that from past few years MI-BCI based systems are developing very fast. MI based BCIs are depends on the accurate classification of different mental tasks such as left-right hand imagery classification [8], left-right leg imagery [9], wrist movement, finger movement [19] etc. It will work as commands for wheelchair or robotic limbs [5][6], so that one can communicates with the external environment only by the imagination of motor action.

This review is organized as follows. In section-2 brief information about block diagram of MI-BCI is explained with each stage of system such as signal acquisition, feature extraction, classification, application and feedback. Section-3 contains a review on previous researches based on motor imagery signal classification. Various feature extraction techniques and classification algorithms are explained with its effects on system accuracy. Overview of available researches and applications are discussed with results, which shows the recent advancement towards the MI-BCI for neurorehabilitation. Comparison of different feature extraction techniques and classification algorithm's accuracy is explained in section-4. Section-5 concludes this review which highlights current challenges and limitations faced by MI-BCI systems. Final Section represents the future scope of MI-BCI system.

2. STAGES OF MI-BCI

Figure 1. shows the general block diagram of BCI system. Signal acquisition, feature extraction, classification and real time application are stages of BCI. EEG signals are recorded from different trials of mental task. These signals are pre-processed and digitized.

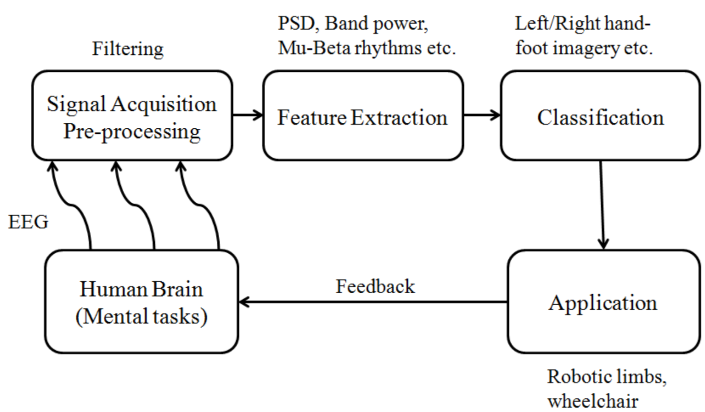

FIGURE 1: Block Diagram of MI-BCI System.

After that signals are fed to the feature extraction stage. Feature sets are used to train/test the classifier. Output of classification is different motor actions. Classifier's output work as the command for the external device such as movement of robotic arm, wheelchair directions (left/right/forward/backward etc.). Feedback is present for the detection of successful communication.

2.1 Signal Acquisition and Pre-Processing

Motor imagery brain signals are recorded from the electrodes which are placed over the human scalp at different lobes of brain: frontal, temporal, central, parietal and occipital. Placement of these electrodes are generally done with the reference of standard 10-20 system [2]. According to application different types of sensors (electrodes) are available such as wet sensor, dry Sensor, multimodality sensor and nano-micro technology sensors [25]. Once these electrodes are placed, then some mental task such as imagine about hand, foot, tongue movements etc. is given to the subject, may be cue-paced (synchronous) or self-paced (asynchronous) and EEG signals are recorded during that trial. For the experimental data collection subjects are trained to control their brain activity.

Electrode placements are generally done with standard 10-20 system of electrode placement. Figure 2. shows the International standard 10-20 system with 75 electrodes. As shown in figure skull is divided into two hemisphere left and right. All the odd numbers of electrodes are on left and even ones are placed on right hemisphere. Signals which are collected from odd electrodes represents left motor movement imagery and even electrodes represent right motor imagery movement. For example signal from C3 electrode has been used for left hand movement and C4 has been used for right hand movement imagination [8][20][21]. Electrodes with the 'z' subscript are reference electrodes. As per the requirement signals are collected from the selected electrodes.

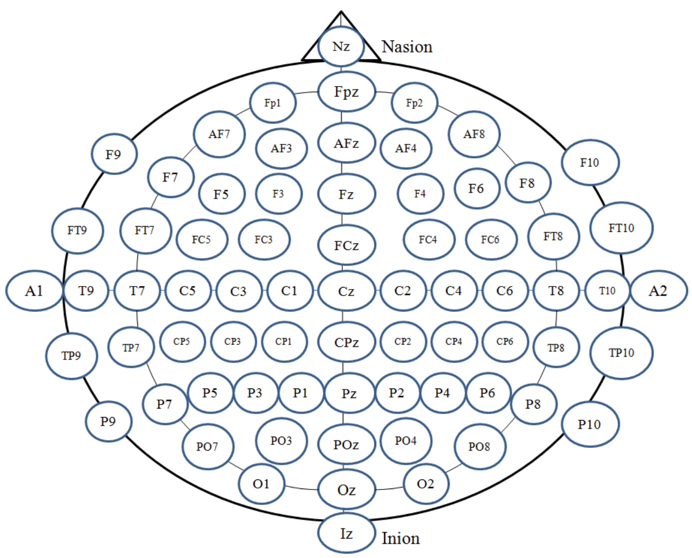

FIGURE 2: Standard 10-20 System with 75 Electrodes.

EEG signals are low voltage variations so needs to amplify first to make it compatible with device. Datasets are prepared by the researchers or also available on some well known open sources like BCI competition [10] and Physionet [33]. EEG signals are divided into different rhythms according to frequency bands like Delta (δ, up to 4 Hz), Theta (θ, 4-8 Hz), Mu/alpha (μ, 8-12 Hz), Beta (β, 13-30 Hz) and Gamma (γ, above 31 Hz). Motor action imagination falls into the mu and beta rhythms. Event-related desynchronization (ERD) and event-related synchronization (ERS) analysis deals with these both brain rhythms [12][13]. Generally the bandpass filters of frequency range 0.5-30 Hz has been used to filtered the EEG signal so that mu-beta rhythms can be preserved in dataset and notch filter is used to remove artifacts-noise [24][25]. Then signals are digitized for analysis.

2.2 Feature Extraction
Digitized signals are now used to extract the different features. For better system performance, more informative features are required. These features reflect the user's intent. More distinct and robust features give better classification accuracy so that system can generate commands. EEG signals are non-stationary in nature due to this reason time domain analysis is not sufficient for feature extraction. Time-frequency and space-time-frequency domain techniques are advanced method of feature extraction, which may give more robust features with compares to analysis in single domain [24].

EEG signals are time varying and non-stationary, so that robustness of features is required for accurate performance of classifiers. Different techniques are available in time domain, frequency domain, time-frequency domain and spatial domain. In *time domain* statistical, Hjorth, auto regressive (AR) parameters has been used to create the feature vector. *Frequency domain* parameters such as band power of mu-beta rhythms, Welch-power spectral density (PSD), averaging power, ERD/ERS are widely used parameters. Different wavelet transforms such as symlets, morlet, daubechies wavelet based energy-entropy and RMS [20][21], empirical mode decomposition (EMD) and short-time Fourier transform (STFT) [23] are used as *time-frequency domain* features. In *spatial domain* principal component analysis (PCA) [9], independent component analysis (ICA) [6], common spatial pattern (CSP) [11][13][14] methods are used.

2.3 Classification
Generated features are used for training and testing of different classifiers. In this stage feature sets are converted into different MI tasks such as left-right hand, foot movement, tongue imagination or word generation etc. It will produce the control signals for external device e.g. Hand MI tasks will work as the directional movement of wheelchair in left-right side or may be the movement of robotic limb. Classification accuracy depends on the robustness of features. Extracted features are fed to classification algorithms such as multilayer perceptron (MLP), support vector machine (SVM) with different kernel functions e.g. (1) radial basis function (RBF) and (2) polynomial, k-nearest neighbor (kNN) and Linear Discriminant Analysis (LDA) are commonly used classifiers [6][9][11][18][20][21]. Some advanced methods of classification are interval type-2 fuzzy system (IT2FS) [19], backtracking search optimization algorithm for neural network (BSANN) [17], genetic algorithm (GA) based neural network (NN) [5] and NN with particle swarming algorithm (PSO) [31] etc.

2.4 Application
Classification of MI-tasks will work as commands for external devices for movement control, locomotion, neurorehabilitation [29]. Main application of MI-BCI is neurorehabilitation. It is useful to restore the motor control of stroke survivor so they can communicate with external environment. Robotic rehabilitation is used to improve their impairments. Some of the application proposed by the researchers are wheelchair control through commands [5], robotic rehabilitation of limb [28], consumer application [26], teleoperated human android robot [27], thought driven robots [30][31].

2.5 Feedback
BCI is depends on the feedback and how precisely one will control their imagination or brain activity in the response of that feedback. Feedback is the essential parameter in brain computer interface system. It will help the users to improve their skill of controlling the neuronal activity. Visual and auditory feedbacks are frequently used as neurofeedback in BCI systems [1][2]. Performance of BCI system is also depends on the training phase of the user. In the training, person learn to control brain activity using different mental tasks such as targeting, selecting and navigating under the presence of biofeedback [25]. In the absence of feedback, user can not develop their skill properly.

3. PREVIOUS RESEARCHES BASED ON MI-BCI
In this section reviews related to the previous research based on classification of MI tasks and different real time applications are discussed. Datasets used for classification analysis are

explained with timing paradigm. All the specifications of datasets are listed briefly such as numbers of electrodes used for signal acquisition, sampling rate, feedback, total trials for training and testing. Feature extraction techniques, classification algorithms and results are discussed with performance parameters.

Left/right hand motor imageries are need to be discriminated precisely because most of applications based on MI-BCI are depends on classification of hand motor imagery. Classification of left and right hand motor imagery was investigated by W. Jia et al. (2004) using event related desynchronization (ERD) [8]. Motor imagery dataset was provided by the Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology Graz in BCI competition II [10]. Database was recorded from one healthy subject (Female, 25-year-old). The task was imagery of left and right hand movement. Figure 3. shows the timing diagram of 9s trial. At t=2s acoustic stimulus indicates the beginning of trial and from t=3s to 9s motor imagery of left or right hand movement was performed according to given cue. The experiment was of 7 runs and 40 trials so total 280 trials each of 9 sec. From that, 140 trials are selected as training and rest are given for testing. Signals are measured from C3, Cz and C4 electrodes. Feedback was based on adaptive auto regressive (AAR) parameters. Using feedback subject learn to control their brain activity during motor imagery signal acquisition. The EEG signals were sampled at 128Hz frequency. Total 1152 samples were provided for each channel and trials. EEG signals were filtered between 0.5-30Hz frequency range.

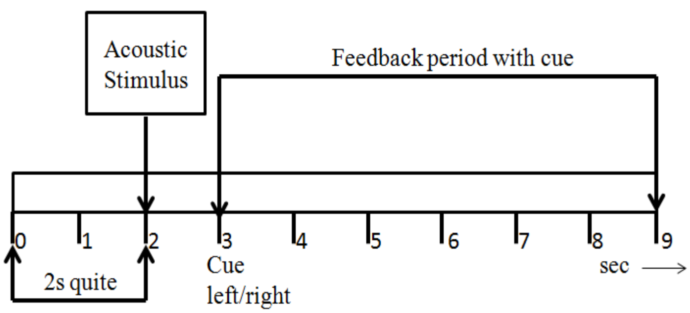

FIGURE 3: Timing Diagram.

Feature set was formed through the event related desynchronization (ERD) analysis. It is a phenomenon in which specific frequency components are suppressed when the subject performing any limb movement or imagine about the movement. ERD of C3 and C4 electrodes were computed for each sample point of trials. Feature vector contains ERD of C3 and C4 electrode. Feature vector using ERD: *[ERD (C3, C4)]*. Size of feature vector for training and testing was 140 rows of trials $\times$ 2 columns of ERD features. Training set was classified by the LDA for each time point and error rate was computed. The time point with lowest error rate gives the optimal time point for classification. Using optimal time point one distance function (time-varying signed distance function-TSD) was computed. If this function achieves negative value for particular trial, then the trial would be classified as left hand imagery. Similarly, for positive values of distance function trial would be classified as right hand imagery. Classification result was evaluated using four performance parameters, minimum error, maximum mutual information, classification time and information transfer rate (ITR). Results using proposed algorithm were: 0.44-bit mutual information (MI), 0.30 bit/s ITR and 15% minimum classification error was achieved in 4.42s classification time. ERD/ERS concepts are based on sensory motor rhythms (mu-beta rhythms). It gives the fruitful results with compares to time-domain approaches. Motor imagery frequencies are variable and ERD/ERS were evoked in different parts of brain which affects the robustness of feature set [3]. It shows that only frequency domain analysis is not sufficient to achieve the high accuracy of the system.

Left and right hand motor imagery can also be classified using statistical, wavelet based and band power features (R. Chatterjee et al., 2016) [20]. Dataset provided by BCI competition II was used in this study. Features were extracted from C3 and C4 electrodes. In *statistical* analysis, along with two basic parameters (1) mean and (2) standard deviation, mean of 1st and 2nd differences are also computed as features. Statistical feature vector constructed by six parameters: mean (μ), standard deviation (σ), mean of absolute values of 1st difference (δ) of raw signal, mean of absolute values of 1st difference ($\bar{\delta} = \frac{\delta}{\sigma}$) of standardized signal, mean of absolute values of 2nd difference (γ) of raw signal, mean of absolute values of 2nd difference ($\bar{\gamma} = \frac{\gamma}{\sigma}$) of standardized signal. Feature Vector using Statistical parameters: *[Mean (C3, C4), SD (C3, C4), Del (C3, C4), Del_bar (C3, C4), Gamma (C3, C4), Gamma_bar (C3, C4)]*. Size of feature set for training and testing was 140 rows of trials × 12 columns of statistical features.

In *Wavelet based energy and entropy*, Daubechies wavelet of order 4 (db4) was used with 3-level of decomposition for computation of energy-entropy of C3 and C4 electrode. Feature vector using wavelet based energy-entropy: *[Wavelet energy (C3, C4), Wavelet entropy (C3, C4)]* with size of 140 rows of trials × 4 columns of energy and entropy features. Size of feature vector was same for training and testing of classifier. Similarly, *wavelet based RMS* is computed for the same order of wavelet and decomposition. Feature vector for wavelet based RMS: *[Wavelet RMS (C3, C4)].* Formed feature vector for training and testing had size of 140 rows of trials × 2 columns of RMS features of C3 and C4 electrodes.

Average power of alpha/mu (8-12Hz) and beta (18-25Hz) rhythms, PSD was calculated by Welch's PSD. To compute the average power Welch's power spectral density is computed along with hamming window of length 64. Averaging of PSD estimation gives average power. Similarly, average power of β-rhythm is calculated. Feature vector using average power: *[Average power of mu rhythm(C4) - Average power of mu rhythm(C3), (Average power of mu rhythm(C3) + Average power of mu rhythm(C4))/2, Average power of beta rhythm(C4) - Average of power beta rhythm(C3), (Average power of beta rhythm(C3) + Average power of beta rhythm(C4))/2]*. Size of feature vector was: 140 rows of trials × 4 columns of average power of alpha and beta rhythms for C3-C4 electrode. *Average band power* of alpha-beta rhythm is the fifth feature vector. It was calculated by computing the power of alpha and beta frequency band. Then average power is estimated by dividing those values by numbers of sample in the particular trial and multiply the result with 100. Average band power was computed for C3 and C4 electrodes. Feature vector for average band power: *[Average band power of mu rhythm(C4) - Average band power of mu rhythm(C3), (Average band power of mu rhythm(C3) + Average band power of mu rhythm(C4))/2, Average band power of beta rhythm(C4) - Average band power of beta rhythm(C3), (Average band power of beta rhythm(C3) + Average band power of beta rhythm(C4))/2]*. So, size of feature vector become 140 rows of trials × 4 columns of average band power features. Here one new approach is applied for average power and average band power. Instead of considering direct values of power, subtraction and mean of average power/band power of C3 and C4 electrode were computed.

All feature sets were classified using two classifiers SVM and MLP. SVM was used with two variant type (C-SVC, Nu-SVC) and four kernels functions (linear, polynomial, radial basis and sigmoidal). MLP was used with 0.7 learning rate and 0.29 momentum. Performance evolution of classification was done by accuracy and receiver operating characteristic (ROC). Using *statistical features* highest result was achieved by RBF-SVM with Nu-SVC variant: accuracy 78.5714 % and ROC 0.786. For *wavelet based energy-entropy* highest accuracy 85% and ROC 0.85 was achieved by linear and polynomial SVM with C-SVC variant. Using *wavelet based RMS* 82.1429 % accuracy and 0.821 ROC for linear-SVM and sigmoidal-SVM with Nu-SVC variant. *Average power* parameters gave 77.1429 % accuracy and 0.771 ROC for linear, RBF and sigmoidal kernel function with C-SVC variant. *Average band power* feature set gave 81.4286 % accuracy and 0.81 ROC using polynomial SVM and Nu-SVC variant. 85.7143% accuracy and 0.9 ROC were achieved by feature set that contains combined set of all feature vectors (140 trials × 26 columns of features) and classified using MLP. Value of ROC is 0.9, it indicates excellent prediction. Results shows that feature vector which consist more than one domain features gives more accuracy than single domain feature set.

According to this study wavelet transform (WT) is found as an efficient parameter for the feature extraction of EEG signals. It gives a better result among all the time and frequency domain approaches. WT is suitable for combined time-frequency domain analysis which cannot be obtained by time and frequency domain methods. Extension of this study is based on effect of wavelets on motor imagery signal classification [21] which is briefly explained further.

Effect of Daubechies wavelet on left and right hand motor imagery was examined by R. Chatterjee et al., 2016 [21]. Same dataset of BCI competition II was used in classification. Wavelet based energy and entropy for C3 and C4 electrodes were calculated as explained above for [20]. Different orders (db1-db10) of Daubechies mother wavelet were used. Feature vector is constructed using each order of wavelet from db1 to db10 with 3-level of decomposition. Three classifiers were used, SVM (polynomial), MLP and Naive Bayes. Performance evolution was done by Accuracy, ROC and F-measure. Result shows that Daubechies wavelet of order 4 (db4) gives a highest accuracy when classified using SVM (polynomial) with Accuracy 85%, ROC 0.850 and F-measure 0.853. Value of ROC is near 0.8, it shows good prediction. In both studies, it is observed that wavelet transform approach is applicable for non-stationary signals like EEG.

Different statistical, PSD, wavelet and ERD based features are discussed above for the classification of left and right hand imagery. Among this all parameters wavelet based parameters are found to be efficient for left-right hand motor imagery classification. Other time-frequency domain techniques such as EMD and STFT are also useful in motor imagery classification. Hybridized technique using multivariate EMD (MEMD) and STFT was proposed to classify left and right hand motor imagery (S. K. Bashar et al., 2015) [23]. Dataset was provided by the BCI competition II for left and right hand motor imagery. To extract the features from C3 and C4 electrodes, MEMD analysis was applied on EEG signals. Samples after 3s were used in analysis. MEMD is an advanced method of EMD in which n-numbers of envelopes are generated by projection of signal in different direction. Average value of these projections gives local mean. By applying MEMD, EEG signals were converted into numbers of IMFs (Intrinsic Mode Functions). 8-frames of STFT were applied on this IMFs and peak value of magnitude spectrum was recorded. STFT is applied on IMF which contributes the maximum energy. In this study, it was found that peak value and entropy of second, third and fifth frames was significantly varying for left-right hand motor imageries, so features of these three frames were used. As a second feature Shannon's entropy was calculated. Instead of using separate values of peak and entropy, multiplication of both features was used to reduce the feature dimensions. Feature Vector: *[max (abs (SN(C3))) × E (abs (SN(C3))), max (abs (SN(C4))) × E (abs (SN(C4)))],* where C3 and C4 are electrodes, S_N indicates output of STFT and N=frame number, *abs* signifies the absolute values and *max* shows maximum value. Size of feature vector was 140 rows of trials × 6 columns of extracted STFT features.

Four classifiers Naive Bayes, different types of Discriminant Analysis, SVM and kNN were used. The highest accuracy was achieved by kNN with k=24 and cosine distance, which is 90.00%. In this novel approach left/right hand imagery is efficiently classified. This time-frequency analysis gives the most activated frequency component in the signal. This method can be applicable for left/right foot, left/right hands and both hands, individual finger movement etc. motor imageries which are difficult to classify. Advantage of this study is distinct feature vector examined by Kruskal-Wallis test and reduced feature vector size. Second advantage is, in this research only those samples of EEG signals were analyzed in which motor imagery was performed.

In spatial domain techniques, common spatial patterns are found to be efficient for binary classification and also useful to reduce the noise artifacts from EEG. To improve the accuracy and computational efficiency of left/right hand motor imagery classification, CSP along with LDA and probability summation was proposed (C.-Y. Chen et al., 2014) [14]. EEG signals were recorded from 32-channel Neuroscan EEG system for left and right hand movement motor imagery. Electrodes were C3, Cz, C4, CP3, CPz, CP4, CP8, T7, T8, TP7, P7, P3, Pz, P4, P8, FC3, FCz, FC4, O1, O2, Oz, FT7, FCz, FT8, F3, F7, Fz, F4, F8, FP1 and FP2. Timing diagram of experiment is shown in Figure 4. Blank screen was provided for 2 seconds at the starting of trial.

After that '+' was displayed from t=2 to 4 seconds then at t=4s arrow either left or right was displayed which indicates the cue for the trial. Motor imagery was ends at t=19 seconds after that picture was displayed on the screen for 7 or 10 second which indicate resting time. Total numbers of training and testing trials were 160 and 80 respectively. Common spatial pattern (CSP) was applied to extract the features. Three datasets were used two are from BCI competition and EEG data recorded by the researchers of this paper. Different classifiers BCILAB, multi band, voting scheme and probability summation were used. Highest accuracy was achieved by the probability summation method for all the datasets. For this study, they had applied LDA with probability summation technique for the classification.

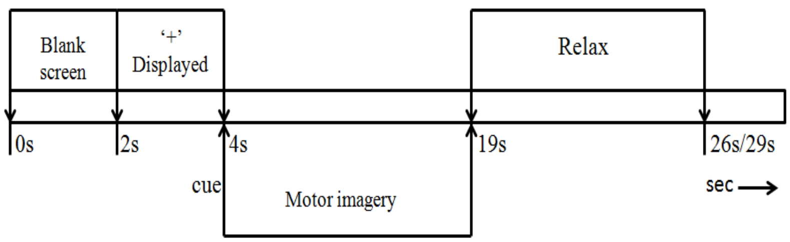

FIGURE 4: Timing Diagram.

Proposed novel algorithm used LDA with probability summation for the classification of feature set. This algorithm was design to overcome the misclassification problem caused by voting scheme. EEG dataset is divided into five frequency bands delta, theta, alpha, beta and 1-30Hz frequency band. For all bands CSP was calculated. LDA with probability summation was applied as a classification algorithm. Achieved accuracy rate of prediction was 91.250%. Motor imagery frequencies are varying from person to person, one of the solution of such a case is CSP. Instead of using features from only two bands alpha and beta, proposed novel algorithm uses all the frequency bands related with motor imagery classification. This algorithm is tested over the 3-datasets with efficient accuracy. Probability summation of left/right imagery movement is new approach used along with LDA which gives a better performance.

In upper limb imagery left/right hand and tongue imageries are widely studied in the development of MI-BCI. Classification of these three motor imageries using time domain features was proposed by M. Hamedi et al. (2014) [7]. Motor imagery signals were recorded from 10 healthy subjects, right handed and 25-34 years of age. Electrode placement was done by standard 10-20 system and experimental data was sampled at 512Hz. Signals were bandpassed between frequency range of 0.5-30Hz and notch filter was used to remove the noise. Signals from 3-electrodes were recorded C3, Cz and C4. Ground electrode was placed at FPz. Two time domain features were extracted (1) RMS and (2) IEEG (integrated EEG). Classification was done by RBF-NN and MLP. Highest accuracy was obtained by RBF-NN & RMS feature, which is 84.94 ± 6.73 with training time 0.53 ± 0.05 sec averaged over 10 subjects. Results of this study were also compared with (Khorshidtalab A. et al., 2012) [34]. Classification of left/right hand, tongue imagery based on Willison amplitude (WAMP) and SVM. WAMP is also the time-domain approach of feature extraction, but using WAMP and SVM 88.96% classification accuracy was achieved. Time domain approaches are not stable for the classification of non-stationary signals like EEG, but among other statistical features WAMP may give better results.

Four MI tasks left/right hand, foot and tongue were classified using CSP features and LDA, QDA, L-SVM and RBF-SVM classifiers (Le Quoc Thang et al., 2014) [13]. In this study, they have used the dataset provided by BCI competition IV 2008, Graz dataset 2A [10]. Dataset was recorded from 9 subjects participated in experiment. 25 electrodes were used from that 22 electrodes are for EEG channels and remaining 3 channels are for Electrooculography (EOG). Only EEG signals are used for the MI classification. There were 2-sessions of 288 trials performed on different days. Each task (left, right hand, foot and tongue) has 72 trials so for each subject total 576 (2 sessions$\times$72 trials$\times$4 tasks) trials were recorded. Figure 5. shows the timing diagram of motor imagery trial. Every trial was starts with the beep. One cue was given on monitor by displaying fixation cross at t=2s. Subjects hold their imagination up to 3.5s and then 1.5-2.5s of resting period is given. The signals were sampled at 250Hz frequency and filtered between 0.5 and 100Hz.

For the feature extraction 500ms afterward data were used and filtered using bandpass filter of 7-30Hz frequency range. Feature extraction was done by applying four CSP filters (one-versus-the-rest) for each MI task. Four filter matrices were calculated. CSP was run for 21 time intervals. Accuracy of classification is depending on the numbers of component extracted from data. In this study theory of exhaustive search was applied to find the best components. These features were classified using LDA, QDA, LSVM and RBF-SVM using one-versus-the-rest scheme and 9-fold cross-validation was applied. Best classification accuracy was recorded for LDA that was 70.18% for training and 58.48% for testing averaged over all subjects, while the classification accuracies using other techniques were approximately 2-4% lower. Highest accuracy was recorded for subject-1, 78.82%. As stated before motor imagery frequencies are varied person to person. CSP has been designed to overcome this drawback. Now days CSP is widely used in MI classification. As a extension of CSP different algorithms were also studied such as Common Spatial-Spectral Boosting Pattern (CSSBP) [16], Common Spatio-Spectral Patterns (CSSP) and Sub-band Common Spatial Pattern (SBCSP).

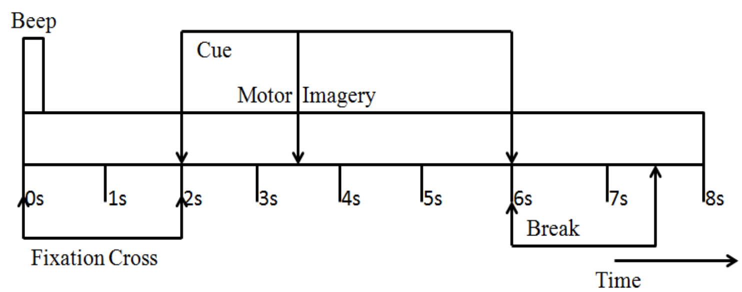

FIGURE 5: Timing Diagram.

BCI competition III provides dataset-IIIa of motor imagery for left/right hand, foot and tongue. EEG signals from total 60-channels were given in dataset. Using different combination of electrodes various two class imageries can be classified (D. Xiao et al., 2009) [22]. Signals were recorded from 3-subjects: K3b, L1b and K6b. Timing diagram of trial is shown in Figure 6. At t=2s acoustic stimulus indicate the starting of trial. At t=3s cue was given to the subject at the same time subject was asked to performed the mental task. 64-EEG channels were used and signals are sampled at 250Hz sampling frequency.

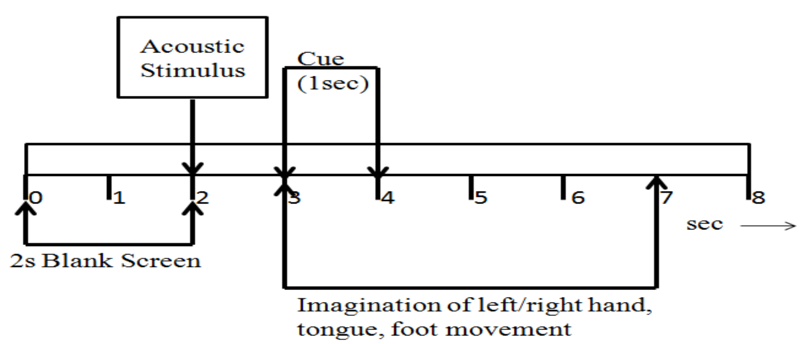

FIGURE 6: Timing Diagram.

Whole database was divided into six types of 2-class problem as listed here, LR, LF, LT, RF, RT, FT (L=left hand, R=right hand, T=tongue, F=foot). Different electrodes (1-60) were used for different combination of tasks and subjects. Time-frequency (TF) analysis was done by computing STFT of signals. Energy entropy was computed to form feature set. Statistical analysis based on Fisher's distance was applied for classification. Highest accuracy recorded for subject K3b was 97.2% for combination of LT at electrodes (17,9), for K6b 95.00% accuracy was recorded for two combinations RF (electrodes 57, 24) and FT (electrodes 45, 6). For L1b 95% accuracy was achieved for three combinations LF, LT and RT at electrodes (23,6), (18,9), (46,10). Averaged accuracy 85% was achieved for six type of combination and 3-subjects. Accuracy of classification is changed subject to subject for the same electrodes. Different combination of electrodes gives variable accuracies in same subject. This is also the new challenge in MI-BCI that which combination of electrodes will be used in system for different MI-tasks classification.

Left, right hand, both hands and both feet motor imageries were classified with various combination of 2, 3 and 4-class MI tasks (H. S. Kim et al., 2013) [11]. Most distinct combinations of MI tasks were found for 99 subjects. EEG motor imagery dataset used in this research was provided by Physionet [33] and recorded using BCI2000 system. Electrode placement was done by standard 10-10 system at 160Hz sampling rate. 109 subjects, with motor imagery left hand, right hand, both fists and both feet. Dataset of 99 subjects were used in study. Timing diagram of trial is shown in Figure 7. At the starting of trial visual cue is available on screen either left or right after that subject was performed the motor imagery task (L/R hand movement) for 4 seconds and then take rest for 4.2 seconds. Again, cue was displayed after resting time may be at top or bottom with reference to that subject were perform either both fists or both feet movement imagery.

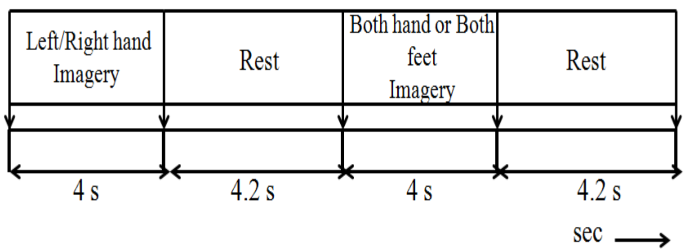

FIGURE 7: Timing Diagram.

EEG signals were processed using EEGLab. Bandpass filter of 6-30Hz frequency was used to filter the raw data. Common spatial pattern technique was used to extracted features of signals. Three CSP patterns per each class were found and log-variance of each pattern was used as feature. LDA was used to classify the different combination of mental tasks. It is a binary classifier due to this reason pair wise approach was applied for multi-class classification. Six combination of 2-class problem (L-R, L-BH, R-BH, L-BF, R-BF, BH-BF), two combination of 3-class (L-R-BH, L-R-BF) and three combinations of 4-class (L-R-BH-BF, L-R-BH-Rt, L-R-BF-Rt) were classified using LDA, L=left hand, R=right hand, BF=both feet, BH=both hand and Rt=rest condition. Maximum mean accuracy was achieved for two 2-class combinations, L-BF with 80.93% and R-BF with 81.96%. There is no significant difference between accuracies of L-BH (77.19%), R-BH (77.60%), L-R-BH-Rt (58.30%), L-R-Bf-Rt (58.30%) combinations. For multi-class motor imagery tasks these results are helpful to find the combination of different mental tasks that gives higher accuracy. Foot/Hand combination is most discriminative class and its classification gives the higher accuracy as compared to others. It is difficult to classify the similar limb movements such as left and right hand or left, right and both hand.

Motor imagery classification for BCI is limited to upper limb imagery only, but for neurorehabilitation of lower limb amputee, classification of foot imagery is required. Classification of lower limbs using kNN and Naive Bayes classifiers was proposed in this study (S. Bhaduri et al., 2016) [9]. Database used in this study was prepared by the researchers using standard 10-20 system of electrode placement. Signals were recorded from 10 healthy subjects (6 males, 4 females, 18-30-year age). During the imagination of lower limb movement motor cortex and parietal lobes are mostly active. EEG signals are acquired from C3, Cz, C4 and P3, Pz, P4 electrodes placed over motor cortex and parietal lobes of brain. Figure 8. shows the timing diagram of one complete trial. Motor movement imagination (left/right foot, no movement) was done in last 3-seconds (t=14s to 17s) before that as indication 2-seconds period of blank screen is provided. Total 2-sessions of 60 trial was performed in which 20 trials for left movement, 20 trials for right movement and rest were for no movement. Data were sampled at 250Hz frequency.

For classification of foot movement imagery five types of features were extracted, four time-domain parameters and one frequency domain parameter. In *time domain* analysis, statistical (mean, variance and standard deviation), Hjorth (activity, mobility and complexity), PCA and AAR parameters were computed. Welch-PSD was used as *frequency domain* feature. Feature Vector for Statistical parameters was: *[Mean (C3, Cz, C4, P3, Pz, P4), SD (C3, Cz, C4, P3, Pz, P4), Var (C3, Cz, C4, P3, Pz, P4)]*. Size of feature set was 40 rows of trials × 18 columns of statistical features. Feature Vector for Hjorth parameters was: *[Activity (C3, Cz, C4, P3, Pz, P4), Mobility (C3, Cz, C4, P3, Pz, P4), Complexity (C3, Cz, C4, P3, Pz, P4)]*. Size of feature was 40 rows of trials × 18 columns of Hjorth features. Similarly, feature set size of AAR parameter for six electrodes was 40 rows of trials × 36 columns of AAR features. Feature set size of PCA parameters was 40 rows of trials × 100 columns of PCA features. For PSD parameter size of feature vector was 40 rows of trials × 174 columns of PSD features. Combination of all feature vector was also used for the classification. Size of combined feature vector was 40 rows of trials × 246 columns of all features. Movement/no movement, left/right lower limb movement were classified using kNN and Naive Bayes classifiers. The best result for left/right lower limb classification was achieved by PSD parameters and kNN (k=7) with 90% accuracy and 0.0531s classification time. For movement/no movement classification highest result was recorded for Naive Bayes classifier with 90% accuracy, 0.4816s classification time using AAR parameters.

There is one limitation of foot imagery classification is that left/right foot imagery classification is not possible using ERD/ERS concept because the cortical areas are too close [3]. So, study on lower limb classification is quite useful in MI-BCI for lower limb rehabilitation because in this research work foot imagery is efficiently classified using PSD features. Most of the studies are based on upper limb rehabilitation. According to [32], in upper limb rehabilitation successful improvement is done by using MI-BCI in 60 hemiplegic stroke patients. For the lower limb rehabilitation or to drive the lower limb prosthetics classification of foot imagery is important.

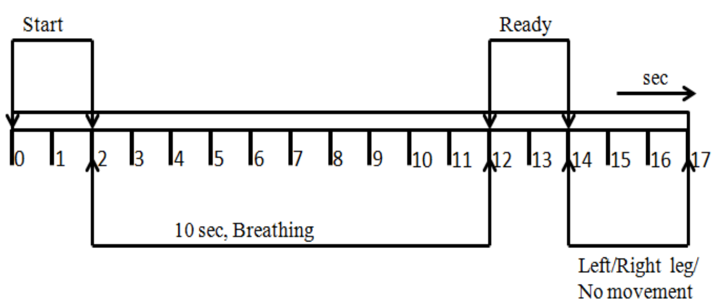

FIGURE 8: Timing Diagram.

NN and fuzzy based technologies are developing nowadays. Such techniques are adaptive in nature so it can be applicable for the motor imagery classification. Backtracking search optimization based neural network classifier (BSANN) was design for classification of three mental tasks: left and right hand movement and generation of words beginning with some random letter (S. Agarwal et al., 2015) [17]. Database used in this study was provided by BCI Competition III with pre-computed PSD features. EEG signals were recorded from three healthy subjects using 32 electrodes with 512Hz sampling rate. Each trial was of 15s for left/right hand imagery and word generation for any random letter. Signals of C3, Cz, C4, CP1, CP2, P3, P2 and P4 electrodes were used in analysis. Features of EEG are already computed using Welch PSD of raw time series data in 8-30Hz band. It was estimated with frequency resolution of 2Hz. Pre-computed feature vector for each subject was a 96-dimensional vector (8 channels times 12 frequency component). Three training set and one testing set was provided for all the subjects. For subject-1 numbers of training samples are 3488/3472/3568 and in testing set 3504 samples are provided. Similarly, for subject-2, 3472/3456/3472 samples for training and 3472 samples for testing, 3424/3424/3440 samples for training and 3488 samples for testing were provided respectively. 4-cross validation technique was applied. 1000 random samples were used as a input of BSANN for each subject. It gives the accuracy of 80.32% for subject-1, 66.03% for subject-2 and 59.34% accuracy for subject-3. In the dataset, large numbers of samples are provided for evaluation, it may take more classification time. Other classifiers such as kNN, SVM and cross-validation techniques are also applicable to classify the given dataset.

Interval type-2 fuzzy classifier (IT2FS) was also proposed to overcome the instability of EEG signals and to overcome the drawbacks of type-1 fuzzy system (T1FS) (S. Bhattacharyya et al. 2015) [19]. Four types of motor imagery tasks were recorded for extension-flexion of wrist and opening-closing of fingers movement. EEG signals were recorded from 8-subjects (4 male, 4 female). Database was recorded by 14-channel Emotiv headset with inbuilt bandpass filter of 0.4 to 45Hz frequency. Signals from F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF3 and AF4 electrodes were used in analysis. Figure 9. (a) and (b) shows the timing diagram of offline training and online testing. After the starting of trial '+' indicates the ready state for 3 seconds than command (cue) was given to the subject for the motor imagery tasks listed above. Online testing includes no-movement imagery and feedback time of 2s. Type of feedback was auditory. It indicates the completion of trial with successful motor action imagination.

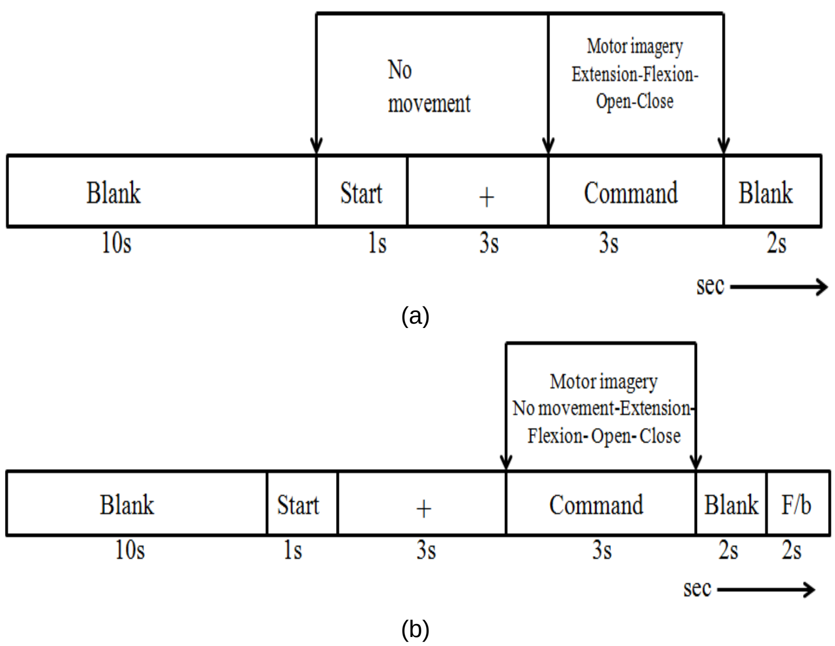

FIGURE 9: Timing Diagram of (a) Offline Training (b) Online Testing.

EEG signals were bandpassed using elliptic filters between 8-25Hz frequency range. Extreme Energy Ratio (EER) was used as feature. It is criterion based on spatial filtering in which energy of spatially filtered signals was computed. Offline and online data classification was done by IT2FS classifier. Two performance parameters were computed, classification accuracy and Freidman statistics (rank). Accuracy was 86.45% in offline mode with 1.25 rank (Classification time 0.8636s) and 78.44% in online mode (Bit rate 1.834bits/min). Fuzzy approach is always designed to adapt the change in input. EEG signals are completely time-varying so for the real-time application adaptive approaches are required. This study also compares the results with some standard classification algorithms such as SVM (65.02%, 5.50 rank), LDA (68.37%, 5.12

rank), kNN (75.28%, 2.75 rank), NB (69.61%, 4.25 rank) and T1FS (79.59%, 2.12 rank). Performance of IT2FS is better than this all classifiers. Combined performance of IT2FS and other feature extraction methods such as wavelet energy-entropy, EMD with STFT, CSP may give better performance.

People who are suffering from neuronal disorders or paralyzed from long time period may not be able to perform motor imagery tasks perfectly, for those non-motor imagery tasks are another solution (R. Chai et al., 2012) [5]. This research work is based on six non-motor imagery tasks such as (1) Arithmetic calculation, (2) Letter composing, (3) Rubik's cube rolling, (4) Visual counting, (5) Ringtone and (6) Spatial navigation. In *Arithmetic calculation (math):* Subjects were asked to imagine solving a series of one by one digit multiplication. *Letter composing (letter):* Subjects were asked to mentally compose a simple letter in mind without vocalizing. *Rubik's cube rolling (cube):* Subjects were asked to imagine a figure of Rubik's cube being rolled forward. *Visual counting (count)*: Subjects performed mentally counting number from one to nine repeatly by visualize the number appearing and disappearing on a blackboard in their mind. *Ringtone (tone)*: Subjects were asked to imagine a familiar mobile ringtone in their head without moving their mouth. *Spatial navigation (navigate):* Subjects were asked to imagine walking around and scanning the surroundings in a known environment.

Database used in this work was prepared by the researchers. 5 able subjects (3 males, 2 females, Age 22-40 years) were participated in the experiment for data collection. 32-channel mono-polar EEG system was used and sampling rate was 256Hz. Signals from only 10 channels C3, C4, P3, P4, O1, O2, T3, T4, A1 and A2 are GND were used. In signal recording session, each subject was asked to perform the any triplet from six non-motor imagery tasks as listed above. Each session was 15 sec long. In further processing first 3 sec data were omitted as preparation time. Moving window segmentation was used over the 12 sec of data and these signals were band passed between 0.1-40Hz frequency followed by notch filter.

Feature extraction of these pre-processed data were done by computing PSD using Fast Fourier Transform. PSD of four frequency bands delta (0-3Hz), theta (4-7Hz), alpha (8-13Hz) and beta (14-30Hz) were estimated for each electrode except GND electrodes. 4 pairs of channel $\times$ 4 combinations on channel $\times$ 4 bands of frequency so total 64 power spectral differences were computed. Similarly, four PSD components of 8-channel were computed, which creates 32 power components. 64-power differences with 32-PSD parameters so total 96 features were extracted. GA based NN was applied to classify any 3-tasks from the six non-motor tasks. Best triplet combination in terms of accuracy & ITR (Information Transfer Rate) was used for commanding wheelchair in left, right and forward directions. Maximum mean accuracy 85% and 0.8 bits/trial bit rate were recorded for triplet of Cube-Count-Tone for subject-4. Each subject had chosen their own triplet for wheelchair commanding. For all five subjects, accuracies and ITR were between 76% to 85% and 0.5 to 0.8 bits per trial. For the better neurorehabilitation, person have to start his/her BCI training before falling in to the completely locked in state (CLIS), because at the late stage of these disabilities person may not be perform the motor imagery tasks as needed [3]. In such cases, non-motor imagery can be applicable.

Classification of four wheelchair commands forward, backward, left and right was proposed by E. Abdalsalam .M et al. (2014) using wavelet based parameters [6]. Database used in this research was prepared by researchers using neuroheadset (Emotiv EPOC). It was a 14-channel headset with standard 10-20 system electrode placement. 14- channels were F3, F4, F7, F8, AF3, AF4, FC5, FC6, T7, T8, P7, P8, O1, and O2. Signals were recorded from five healthy subjects (Age 26-35 years). For the experimental data collection subjects were asked to imagine task of wheelchair direction: left, right, forward and backward for given trial period. These signals were sampled at 128Hz. EEG signals were pre-processed in EEGLab, pass band filter of 1-20Hz and as a artifacts removal technique ICA and linear filters were used. Feature extraction was done using WT. Two wavelet families Daubechies (db4) and Symlets (sym4) were used with order 4. EEG signals were decomposed into delta, theta, alpha, beta and gamma frequency component.

Alpha and beta frequency components were used as classifiers input. MLP, simple logistic and bagging classifiers were applied. Highest accuracy was achieved by db4 wavelet and simple logistic classifier which is 80.4%. Wavelets has been found superior in MI classification with other time and frequency domain approach. As we noticed in review of [20][21] that Daubechies wavelet of order 4 gives a better accuracy. In this research Daubechies wavelet (db4) is found to be a better feature extraction technique.

All the real-time application such as wheelchair and robot control needs efficient classification of motor imagery tasks. Generally, research datasets are prepared in cue-paced mode of trials, in which user follows the cues given by investigator of experiment. In practical application, all the motor imageries are asynchronous or self-paced, so robust techniques of feature extraction and classification is required to drive a control device online. Humanoid robot control application for forward, left and right directional movement of HuroEvolutionAD robot was investigated using PSD features and NN classifier (N. Prakaksita et al., 2016) [31]. Three motor imageries were used to command the humanoid robot. Tongue movement for forward directional movement, left-right hand imageries are for left-right turn of robot. Motor imagery EEG was recorded using Emotiv headset of 14-channel and 128Hz sampling frequency. 14-electrodes are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 according to 10-20 system. Timing diagram of experiment is shown is Figure 10. Trial of 8 seconds was divided into 3 parts of 2s, 3s and 3s. Last three seconds were provided for MI imagination from given three tasks (left/right hand/tongue). After completion of motor imagery resting time of 2s was given. Total 15-trials of each motor imagery were recorded for training.

EEG signals from 2-channel FC5 and FC6 were used for feature extraction. Welch's-PSD of mu rhythm was computed for this two channel. Maximum and average power at every 2Hz in 8 to 16Hz band were used as the classifier input. NN with particle swarming algorithm (PSO) was used. In online testing HuroEvolutionAD humanoid robot was used for 15-trials of left/right hand and tongue motor imageries. It walks forward when classifier gives output as tongue imagery. It turns left/right with respect to classification output of MI task as left/right hand imagery. In training mean accuracy was 88.8% and in testing mean accuracy was 91% averaged over all classified trials of left, right hand and tongue imagery. Results of PSO-NN techniques was compared with well-known classifiers such as LDA, Naive Bayes, L-SVM and NN. Using LDA, Naive Bayes, L-SVM, and NN, 42.2%, 66.67%, 63% and 77% accuracies were recorded respectively. Among these all NN with PSO gives 91% accuracy.

In [17] and [31] NN classifier with weight optimization techniques were proposed for classification of MI tasks. With compares to BSA, PSO gives the better accuracy of 91% to classify the three-class problem in online as well as in offline mode. All the real-time MI-BCI are in online mode so to achieve efficient performance of MI-BCI adaptive algorithms can be applicable, but whenever we are working with NN training time is crucial parameters. Drawback of NN classifier is long training time required for large feature sets.

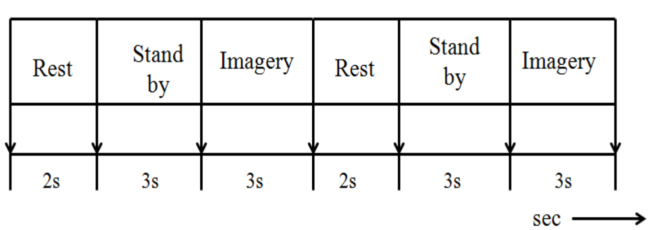

FIGURE 10: Timing Diagram.

Proposed by	Dataset	Subjects	Imagery Movement	Features	Classifier	Accuracy	Year
S. K. Bashar et al.[23]	BCI Comp. II	1	Left/right hand	MEMD+STFT	kNN	90%	2015
R. Chatterjee et al.[20]	BCI Comp. II	1	Left/right hand	Statistical, WT, Average Power, Average Band Power	MLP SVM (Polynomial, Linear)	85.7143% 85%	2016
R. Chatterjee et al.[21]	BCI Comp. II	1	Left/right hand	Wavelet Energy, Entropy	Naive Bayes MLP SVM(Polynomial)	80% 83.5714% 85%	2016
C.-Y. Chen at el.[14]	Prepared by Researchers	5	Left/right hand	Common Spatial Patterns	LDA + Probability summation	91.250%	2014
M. Hamedi et al.[7]	Prepared by Researchers	10	Left/right hand, tongue	RMS, IEEG	RBF-NN	84.94±6.73%	2014
N. Prakaksita et al.[31]	Prepared by Researchers	1	Left/right hand, tongue	Welch's PSD	NN with PSO	Offline: 88.8% Online: 91%	2016
S. Agarwal et al.[17]	BCI Comp. III	3	Left/right hand, word generation	Welch's PSD	NN with BSA	68.563%	2015
Le Quoc Thang et al.[13]	BCI Comp. IV	9	Left, right hand, foot, tongue	Common Spatial Patterns	LDA	Training:70.18% Testing:58.48%	2014
D. Xiao et al.[22]	BCI Comp. III	3	Left/right hand, foot and tongue	STFT based Energy-Entropy	Statistical Analysis based on Fisher's distance	85%	2009
H. S. Kim et al.[11]	Physionet	99	Left, right hand, both hands and both feet	Common Spatial Patterns	LDA	81.96% (Right hand/both Feet)	2013
S. Bhattacharya et al.[19]	Prepared by Researchers	8	Extension/Flexion of wrist, Open/close fingers	Extreme Energy Ration	IT2FS	Online:78.44% Offline:86.45%	2015
S. Bhaduri et al.[9]	Prepared by Researchers	10	Left/right foot	AR, PSD, Hjorth, Statistical, PCA	Naive Bayes kNN	87.50% 90%	2016
E. Abdalsalam et al.[6]	Prepared by Researchers	5	Wheel chair: Left, right, forward, backward	Daubechies and Symlets Wavelet parameters	Simple logistic MLP Bagging	80.4% 72.2% 76.3%	2014
R. Chai et al. [5]	Prepared by Researchers	5	Arithmetic calculation, Letter composing, Rubik's cube rolling, Visual counting, Ringtone, Spatial navigation.	PSD	GA based NN	76%-85%	2012

TABLE 1: Performance comparison of various feature extraction techniques and classifiers.

4. COMPARATIVE ANALYSIS

Table 1. shows the summary of numerous feature extraction techniques and classification algorithms proposed for classification of different motor imagery tasks. First four studies are based on left/right hand motor imagery classification. In [20][21][23] same dataset from BCI competition II was used. Highest accuracy (90%) was recorded for MEMD with STFT features and kNN classifier. CSP feature and LDA with probability summation classification approach was proposed in [14] for self-acquired dataset of left/right hand motor imagery, 91.250% classification accuracy was recorded in this study. According to this observation MEMD with STFT and CSP features were found to be an efficient technique of feature extraction to discriminate between left/right hand motor imagery. Left/right hand and tongue motor imagery was efficiently classified in [7][31]. 84.94$\pm$6.73% classification accuracy was achieved by RMS and IEEG features with RBF-NN classifier. Welch's PSD and NN with PSO gives 88.8% accuracy in offline mode and 91% accuracy in online mode. For the lower limb rehabilitation left/right foot imagery was classified using PSD parameters and kNN classifier with 90% accuracy [9]. In movement/no movement classification of foot 90% accuracy was achieved using AAR features and Naive Bayes classifier.

Classification of four non-motor imagery tasks left, right, forward and backward movement for wheelchair commands [6] were classified using Daubechies and Symlets wavelet parameters. Three classifiers simple logistic, MLP and bagging were applied for classification. Using simple logistic classifier 80.4% average classification accuracy was achieved for 5-subjects. Different non-motor imagery listed in [5] were classified using PSD features and GA based NN classifier. Triplet of three non-motor task Letter-Tone-Navigate was classified with 82% accuracy. Similarly, Math-Count-Navigate, Math-Letter-Navigate, Cube-Count-Tone and Math-Letter-Cube were classified with 84%, 76%, 85% and 81% average accuracy respectively. Fuzzy based classifier [19] was proposed for the classification of extension/flexion of wrist, open/close fingers, 78.44% online accuracy and 86.45% offline accuracy was achieved using EER features with IT2FS classifier. Four class motor imagery classification for left/right hand, tongue and foot movement was proposed in [13] using CSP features and LDA classifier. 70.18% and 58.8% accuracies were recorded for training and testing. Various 2-class combination of motor imagery tasks were classified using STFT based energy-entropy and Fisher's distance based classifier [11]. LR, LF, LT, RF, RT and FT combinations were classified, among this for subject-1 best discriminative combination of task was LT with 97.2 % of accuracy. For subject-2 RF, FT and for subject- 3 LF, LT, RT were classified with 95% accuracy. Averaged 85% accuracy was achieved for six type of combinations and 3-subjects. Classification of various 2-class motor imageries: L-R, L-BH, R-BH, L-BF, R-BF, BH-BF, 3 and 4 class motor imageries: L-R-BH, L-R-BF, L-R-BH-BF, L-R-BH-Rt, L-R-BF-Rt were classified using CSP features with LDA classifier. The best distinct combination among this all was R-BF with 81.96% classification accuracy [11].

Literature review shows that MEMD, STFT based energy-entropy, PSD, wavelet based energy-entropy and CSP features are found to be efficient for feature extraction of EEG signals. LDA and kNN classifiers are widely used for classification of different MI-tasks. NN and fuzzy based classifiers are also useful for practical applications of BCI system.

5. CONCLUSION

Researches on electroencephalographic non-invasive MI-BCI is developing exponentially from past decades. Upper limb MI classification were successfully done in many studies which is useful in neurorehabilitation of stroke patients and person having neuronal disabilities like spinal cord injuries. Most of studies are based on healthy subjects and previously recorded database. More studies need to be done with stroke patient's database which makes the MI-BCI system more effective in clinical area. Studies indicate that currently MI-BCI is limited to upper limb imagery only. Lower limb rehabilitation is also required to provide quality life to disabled people. For the neurorehabilitation, patients must start his/her training before late stage of disease because after suffering from long time disease person may not able to perform motor imagery tasks as needed. Scalp recorded EEG signals are noisy and have lower resolution then ECoG but it is quite safe for the people due to no harm or infection as well as no neurosurgery is required. Different electrodes were placed in EEG recording, which combination of electrodes is used in feature extraction is also affect the performance of the system because each region of brain cannot be work as an isolated unit. Robust-Informative feature extraction techniques are still the challenging issue because motor imagery frequencies are variable. Some spatial and frequency domain techniques such as CSP, PSD and WT are found to be informative in MI-classification. At the classification stage, some adaptive approaches are required for better classification. Fuzzy and NN based technologies are developing nowadays which can be useful in MI classification. All the real-time applications are depending on the accurate classification of MI-tasks.

6. FUTURE PERSPECTIVE

Brain Computer Interface is useful to provide non-muscular channel by designing robotic devices. Most of BCI systems are under the research. To implant such a system practically, biocompatible signal acquisition devices, real time computational algorithms, feedback and designing of artificial robotic limbs are vital stages of BCI [35]. In future patients can drive a robotic prosthetics as part of their body using MI-BCI, if different stages of BCI are efficiently designed. Review shows that algorithms are tested on datasets of healthy subjects. To develop the system which provides the communication capabilities to patients, database of stroke survivors and paralyzed patients must be analyzed. Behavior and characteristics of survivor's electrophysiological signal need to be investigated. BCIs have vast future because no alternative is available for rehabilitation of patients [2]. Among the clinical research and rehabilitation, it can be used to operate domestic devices and video games.

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