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A Review on EEG Based Brain Computer Interface Systems

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ABSTRACT*— A Brain Computer Interface (BCI) system takes and classifies a user's brain activity into a signal to which a computer can respond. To control a BCI, the user should produce various brain activity patterns which are captured in form of Electroencephalogram (EEG) and converted to commands by identifying the patterns by the system. Such classification was undertaken by various methods, and performed by machine learning algorithms; the most common being Multilayer Perceptrons. To begin with BCIs provided those with severe physical disabilities ways to communicate/interact with computers. Most of the BCI research focused on able-bodied users and EEG based BCI systems. Many papers that are published on BCIs are more theoretical than actual implementation of actual system. This paper, surveys various BCI systems available in literature.*

KEYWORDS—*Brain Computer Interface (BCI), Electroencephalogram (EEG), Evoked Potentials*

I. INTRODUCTION

A Brain-Computer Interface (BCI) is a communication system where a subject forwards commands to an electronic device through brain activity alone [1] without any peripheral muscular activity [2]. Such systems allow for communication for those affected by motor disabilities [3]. To control a BCI, the user should produce various brain activity patterns which are captured in form of Electroencephalogram (EEG) and converted to commands by identifying the patterns by the system. In most BCI, the identification of pattern is based on a classification algorithm [4], i.e., an algorithm that automatically estimates the class of data represented by a feature vector of the EEG [5]. Because of growing interest for EEG-based BCI, many published results are related to investigation/evaluation of classificationalgorithms.

Many paradigms for constructing EEG-based BCI systems were tried out in the last 20 years. The paradigms vary from well-known phenomena occurring in EEG when interacting with stimuli, to the use of biofeedback, to paradigms using sophisticated machine learning algorithms to classify the EEG. Each approach has its advantages and disadvantages.

BCI system building paradigms use specific changes in EEG that occur through presentation of controlled external stimuli and they were implemented with great success. As these EEG changes were through a stimulus, they are called Evoked potentials. For example, many BCI systems were built that utilized Steady-State Visually Evoked Potentials (SSVEP) which can be elicited by ordering the subject to fixate on a box/checkerboard on an LCD screen flickering steadily. A corresponding power increase is identified in the subject's EEG at the same frequency and in the flickering's harmonic frequencies. SSVEP can control a computerized device by flickering many different stimuli at various rates while at the same time allowing a user to shift his/her gaze between different stimuli [6]. BCI systems operating thus proved to be effective, with research suggesting that a SSVEP speller system which achieves information transfer rates as high as 62.5 bits per minute (bpm) with minimum user training [7] can beconstructed.

Another EP type commonly used for constructing BCI systems is called the P300, which is an EP that occurs after presentation of rare-but-expected stimulus. The P300 is called so as it appears in EEG signals as a positive deflection roughly 300ms following stimulus' onset. An example of BCI system utilizing the P300 is the P300 speller, where a grid of numbers/letters is shown to the user on a LCD screen. Rows and columns of this grid are flashed pseudo-randomly. A P300 is evoked when the user attends to a single character in the grid, as the character flashes infrequently and at intervals which he subject does not know [8]. The BCI then determines which character the user attended by tracking each row and column when flashed. Studies reveal that the P300 speller can be successfully used, with information transfer rates as high as

13.3 bpm being achieved in subjects with amyotrophic lateral sclerosis and 11.3 bpm in healthy subjects [9].

Though EP approaches achieve impressive results, they have some fundamental imitations. As the BCI user has to receive some stimulus, they might be distracted from tasks they want the computer to perform or the message to be communicated.

It is hard to think, for example, that a subject can control an electric wheelchair or prosthetic device while attending at the same time to a visual stimulus on an LCD screen. Also methods which need a subject to carefully manipulate their gaze may be impractical for those with certain disabilities. Users might not be able to focus on visual stimulus. Lastly, BCI users might find repeated presentation of a stimulus, unpleasant orirritating.

One way to avoid problems in EP utilizing paradigms is to classify spontaneous EEG not directly linked to external stimulus. For this, many developed BCI systems which exploited subject's ability to wantonly manipulate their μ (8-12Hz) and β (13-28Hz) rhythms in EEG recorded over sensory-motor cortices. For example, Wolpaw, et al., [10] explored BCI systems that train users to alter the power of their μ and β rhythms through biofeedback. Similarly, Pfurtscheller, et al., [11] explored techniques to operate BCI systems where users issue commands through performance of imaginary motor tasks. These are also linked to changes in μ and β rhythms. These works combine both use of biofeedback and machine learning. Though such mutual learning improves user's ability to use BCI systems, it makes comparisons with other approaches difficult.

Further generalizing on classifying EEG recorded during imagined motor imagery, Keirn, et al., [12] suggested EEG classification recorded in broader set of imagined mental tasks. The imagined tasks to be classified were chosen typically to be neurologically different. For example, mental tasks used by Keirn, et al., included complex problem solving, geometric figure rotation, mental letter composing and visual counting. Here, a user had to command a BCI system through performing imagined mental tasks associated with the desired command before training. Research by Galan, et al., [13] proved that this paradigm can successfully navigate an electric wheelchair equipped with laser range-finders through an obstacle course.

EEG classification recorded during imagined mental tasks are hard for many reasons. First, EEG patterns in such tasks vary widely across subjects and even for the same subject at different times. Second, a subject could perform more than one task simultaneously without being aware of doing so. For example, a subject might be visualizing numbers in a counting problem overlapping another visualization task. Finally, it is unclear as to whom and for what mental tasks EEG signals have enough information for task discrimination. Even so this paradigm is appealing as it offers greater freedom to BCI users and also because it needs no externalstimulus.

The application of BCI is numerous. BCIs were first used in assistive technology applications where BCI systems helped people suffering from locked-in syndrome. Before BCIs they had limited chances at communication. BCI supports people with severe physical disabilities through a system which permits people to browse the web with their minds. People with such physical disabilities cannot manipulate a mouse successfully to select small things like a hyperlink. New interface design paradigms are developed to enable a BCI system to browse the web. BCI use for gaming and other entertainment types is relatively new. Most work in this area is about theoretical designs/testing new BCI features [14, 15]. Section II reviews some of the recent work in literature related to EEG based BCI systems.

II. FEATURE SELECTION

A. *Bispectrum based FeatureExtraction*

Features were extracted using higher-order statistics based on an EEG signal bispectrum. Zhou, et al., [16] suggested characterizing of the temporal and frequency information in EEG data using hybrid features. The following hybrid features were extracted:

(1) Four coefficients of the AR model obtained by the Burg method.

(2) Four features related toPSD:

(i) peak frequency of thePSD;

(ii) peak value of thePSD;

(iii) the first-order spectral moment of thePSD: $m_1(PSD) = \sum K.PS_K$ Where K=0 toN

and

(iv) the second-order spectral moment of the PSD: $m_2(PSD) = \sum (K-m_1)^2.PS_K$ Where K=0 toN

(3) Four features based on the third-orderstatistics:

(i) the sum of logarithmic amplitudes of the bispectrum

$H_1 = \sum \log(\left| B_x(w_1,w_2) \right|$,where w_1,w_2 € F where F is the frequency range considered.

(ii) the sum of logarithmic amplitudes of diagonal elements in thebispectrum

$H_2 = \sum \log(\left| B_x(w,w) \right|$,where w € F

(iii) the first-order spectral moment of the amplitudes of diagonal elements in thebispectrum

$H_3 = \sum \log(|B_x(w_k,w_k)|$, Where K=1 to N

(iv) the second-order spectral moment of the amplitudes of diagonal elements in the bispectrum

$H_4 = \sum (K-H_3)^2 \log(|B_x(w_k,w_k)|$, Where K=1 to N

The above features are extracted for all the channels at every sampling point using a sliding window.

B. Feature Extraction by Multi-Layer Perceptron(MLP)

The Multi-Layer Perceptron (MLP) network shown in the fig 1 consists of 5 layers (one input layer, three hidden layer and one output layer) with different semantic. The input layer represents the raw EEG signal. The first and second hidden layer represents the creation of channels and the subsamples and filters the signal respectively. Cecotti and Graser [17] proposed a feature selection strategy founded on important connexions in the first hidden layer of a NN with five layers trained with all electrodes as input. A new classifier is generated with respect to the remaining topology and desired electrodes for thesystem.

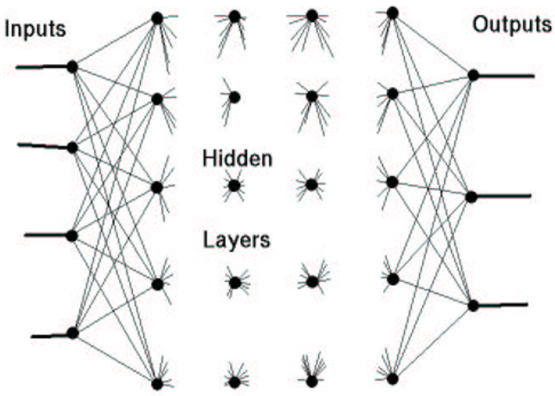

Fig. 1 A Simple Neural Network

In the first hidden layer, the information of the most relevant electrodes is extracted. The power of the electrode i is computedas

$\varepsilon_i = \sum_{j=0 \text{to} N} | w(i,j) |$

The discriminative power of the electrode is considered to be low when weight is close to 0.

C. Feature Extraction by Self Organizing Fuzzy Neural Network

Four Self-Organizing Fuzzy Neural Networks (SOFNNs) coalesced and performed one-step-ahead predictions for a EEG time series data. Features were derived from Mean Squared Error (MSE) in prediction or mean squared of predicted signals (MSY). Coyl, et al., [18] presented a new Feature Extraction Procedure (FEP) to extract features from EEG recorded from subjects who produced right and left motor imagery.

$= \frac{1}{M} \sum_{t=1}^{M} (y(t) - \hat{y}\, k(t))^2$forMSE fy_k

$= \frac{1}{M} \sum_{t=1}^{M} (\hat{y} k(t))^2$forMSY

The extracted input-output data vector for the time series a3 and fy_k a4 are shown in fig 2.

III. CLASSIFICATIONALGORITHM

A. Linear Discriminant Analysis (LDA)classifier

LDA firstly maps the data (feature vector) x to be classified by the following linear transformation:

$Y= w^T x + w0;$

Where w and w0 are determined by maximizing the ratio of between-class variance to within-class variance to guarantee maximal separability.

B. Support Vector Machine (SVM)classifier

The output of a binary Support Vector Machine classifier in fig 3 can be computed by the following expression:

$y = \text{sgn}(\sum \alpha i\, y_i k(x_i,x)+b$

Where i=1 to N, (xi,yi) are the training samples [a3(t-4),a3(t-3), a3(t-2), a3(t-1): a3(t)]

[a4(t-4), a4(t-3), a4(t-2), a4(t-1); a4(t)]

INPUT SIGNALS

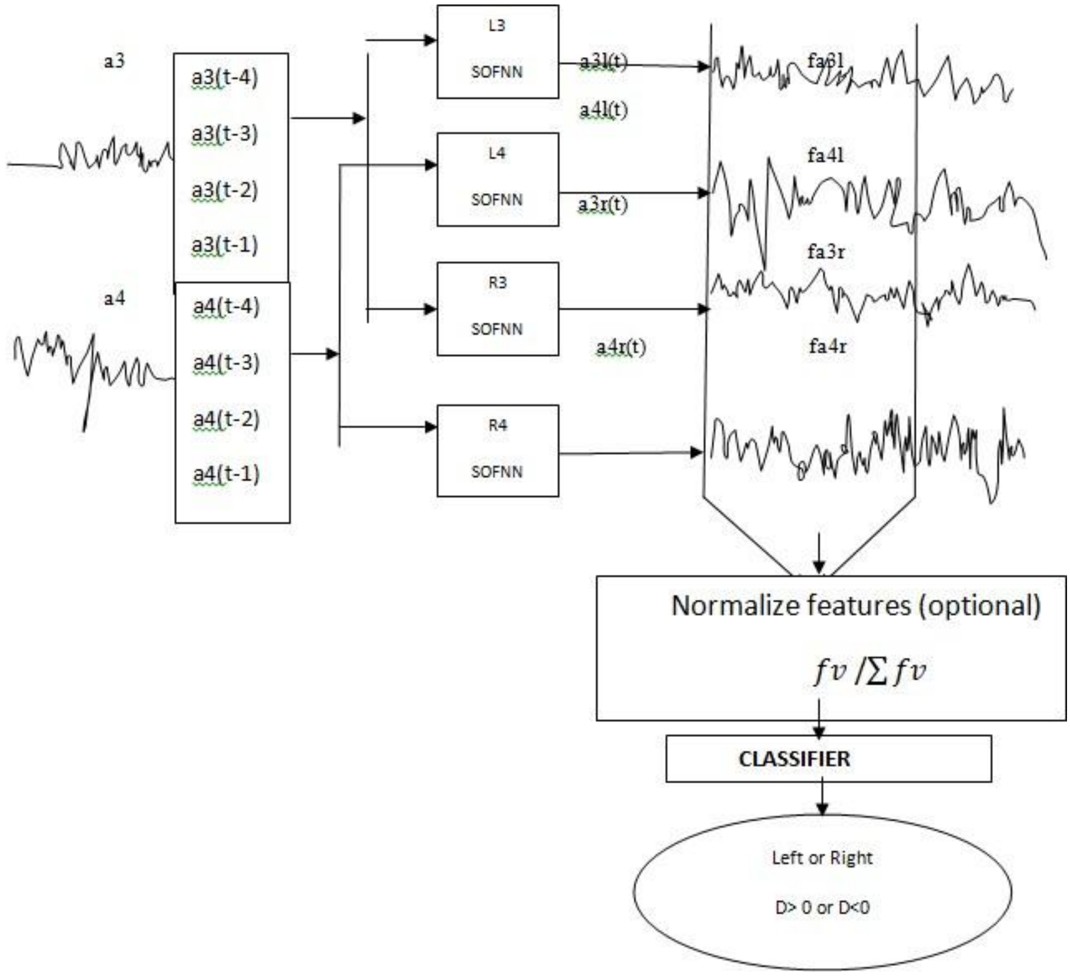

Fig 2: Complete Architecture of BCI

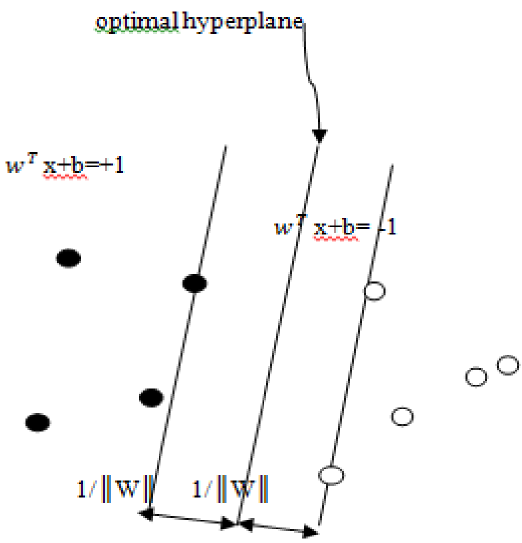

Fig 3: Support Vector Machine

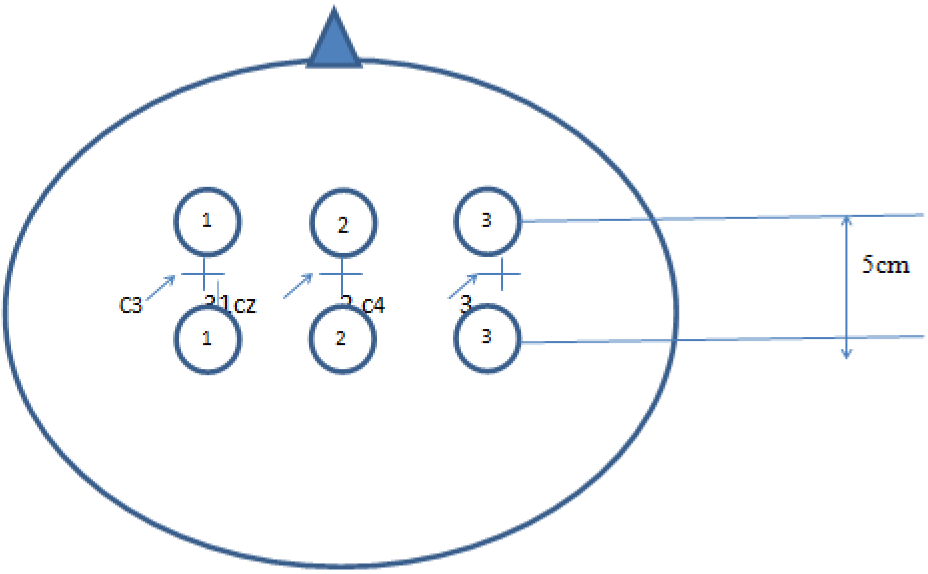

Fig 4: Electrode Positions

To ensure classification accuracy and confidence on the Graz BCI data set in BCI-competition 2003 entropy based mutual information from classifying results was the criterion to compare performance of various methods. Greater MI of classifying results through a classifier indicated that it produced higher confidence results. To characterize non-Gaussian information in EEG signals, a new feature extraction system founded on bispectrum was suggested and applied to right and left motor imagery classification to develop EEG-based BCI systems.

In trials on a PC with Dual Core CPU, it took 3.14 ms to extract features from among 256 sampling points on a pattern. Hence, this feature extraction method could be applied in real-time mental classification tasks. In 280 trials, 140 labeled trials trained the classifier. The test data set was kept away from feature extraction and classifier training. Experimental results on Graz BCI data set revealed that on the basis of the proposed features, LDA, SVM and NN classifiers outperformed the winner of the BCI 2003 competition on same data set with respect to mutual information, competition criterion and misclassificationrate.

The recognition rate of P300 speller over two subjects was 87% when considered with only 8 electrodes. This paper focused on P300-BCIs, which utilize visual evoked potentials as brain responses. The signal is measured by electrodes covering the parietal lobe shown in fig 4. The detection of a P300 wave is equal to detection of where a user looked 300ms before detection. The electrodes location where a signal has high intensity is dependent on the subject. For non-experimental BCI, it is impractical to cover the entire head with electrodes. The electrodes position and number must be selected carefully. An electrodes choice corresponds to a feature selection problem. As expected and similar to the P300 detection, results were lower than when all 64 electrodes were use. The P300 response precision is improved when electrodes are selected under the new strategy. Recall is improved for subject B. But these detection improvements are translated for subject A, which provides improved results in character recognition when compared to a fixed electrodes choice. This is explained by concentration of concerned electrodes in specific locations. As information is dispersed more and homogeneous with subject B, the electrode selection impact has reduced importance. However, half the selected electrodes are common for both subjects and the set of pre- defined electrodes. This process tested on database 2 of the third BCI competition, provided excellent results(94.5%).

Network weight analysis is consistent to neuro-scientific knowledge. A relevant subset of electrodes can be selected by pruning the network as this strategy ensures a recognition rate of 87% with just 8 electrodes. Classification was performed through a LDA. This new FEP was tested on three subjects offline with classification accuracy rates touching 94%. The procedure requires minimum subject specific data analysis and also shows potential for online feature extraction and autonomous system adaptation.

IV. BCI PREPROCESSINGMETHODS

A. Independent Component Analysis(ICA)

The Independent Component Analysis (ICA) decomposes a mixed signal into its statistically independent components. EEG signals can be decomposed by ICA. For proper decomposition, ICA assumes that the number of sources is equal to the number of sensors, source signals are statistically independent (at most only one source having a Gaussian distribution), and there is no time delay between source and measurement sites. Two important preprocessing steps in ICA are Centering and Whitening. Centering subtracts the mean values of the signals so that they have zero means and in whitening by a linear transformation results in uncorrelated signals with unit variance.

B. Matching Pursuit (MP)Algorithm

Matching Pursuit (MP) decomposes the EEG into several components. The decomposition is achieved by selecting from a dictionary of Gabor signals. The signals in dictionary with high correlation with the input EEG are selected and subtracted from it. The process is repeated till the ECG signal is represented by dictionary components. The MP software developed at the Warsaw University is used for the analysis.

Rao, et al., [19] analyzed ICA and MP method's effectiveness for use in EEG preprocessing and TDNN classification. This study used practical settings, the deflation method and Gaussian nonlinearity for fixed-point algorithm. Due to input signals nature, sometimes ICA does not converge even after many iterations and this is referred to as a stroke. But, in this a stroke situation was avoided through a built-in stabilization algorithm which ensured convergence after 1000 iterations. The authors used the EEG data set provided by Colorado State University containing EEG recordings from 7 human subjects in five mental task trials: baseline (rest), multiplication, letter composing, rotation, and counting.

Each trial was undertaken 5 times and data was recorded from electrodes: c3, c4, p3, p4, o1, and o2. There was also a 7th channel which contained EOG data discarded earlier in this study and used a 6th order Butterworth filter to remove 60 Hz line interference. Every data passage had 2500 samples created via a 10 second recording of a mental task with a sampling rate of 250Hz. The neural network classifier was developed with MATLAB 7 neural network toolbox version 4. It was seen that ICA was better than MP in reducing neural network classification error; but the advantage was not much.

C. Welch'speriodogram

Welch's procedure is to estimate the PSD of a stochastic signal combines windowing and averaging in order to obtain smooth spectrum estimation without random fluctuations resulting from the estimation process itself.
The original data sequence of each channel is divided into a number *K* of possible overlapping segments. A window *u(n]* is defined over each of these segments and the corresponding periodograms are computed and then averaged.
If *z@)[n*re*]*p resents the sample *z[n]*of the kth data segment (of length *N*), then the modified periodogram for that segment is defined as
It was generally agreed for this simulation that the usual method of partitioning data vectors into two sets - using 75- 80% of available vectors for training and the remaining for testing -, might be too conservative for a few classifiers.

V. BCISYSTEMS

A. P300BCI

P300 was one type of BCI signals where only in past few years there was a strong increase in P300 BCI research. Fazel-Rezai, et al., [21] discussed about P300 BCI trends and challenges. The current status of P300 BCI technology has been discussed in proposed method, and then about new directions such as paradigms for eliciting P300s, signals processing methods, applications and hybridBCIs.

$\hat{P}x^{(k)}(w) = \frac{1}{N}\left|\sum_{n=0}^{N-1} v\lfloor n\rfloor x^{(k)}\lfloor n\rfloor\, e^{-jwn}\right|^2$, k=1, ,K

Where w = 27rf (in rad/s) is the angular frequency and the window *U* should obey the following (normalization) property$\left(\frac{1}{N}\right)\sum_{n=0}^{N-1} v\lfloor n\rfloor^2$=1

Then the estimate of the PSD of the signal, for each frequency *w*. is taken as

$$\hat{S}_x(w) = \frac{1}{k}\sum_{k=1}^{k}\hat{p}x^{(k)}(w)$$

Barreto, et al., [20] suggested that a simple and powerful pre-processing method that was capable of handling noisy and non-stationary natures of EEG signals - while maintaining useful information – could alleviate problems faced by classifier design. The authors suggested use of Welch's periodogram as a good feature extractor, comparing performances of SOM and MLP-based neural classifiers with the standard Bayes optimalclassifier.

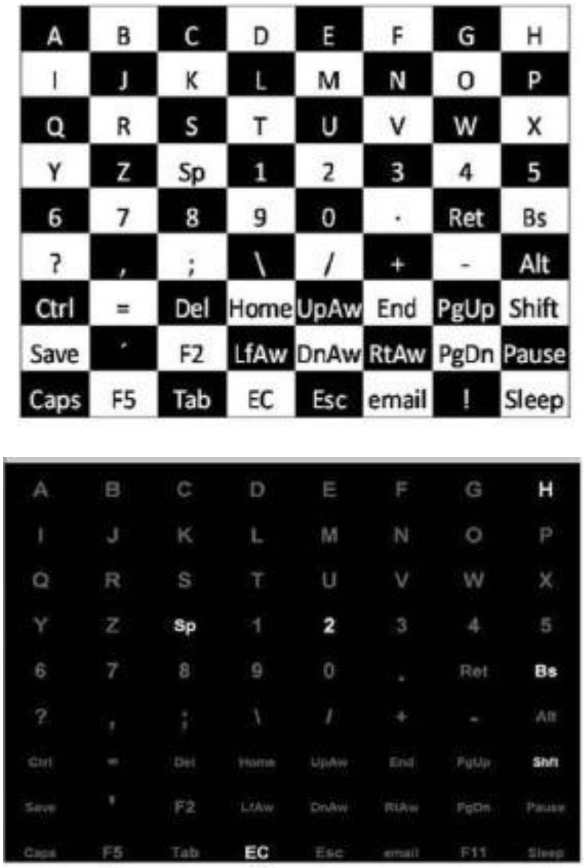

Fig 5: Checkerboard Paradigm

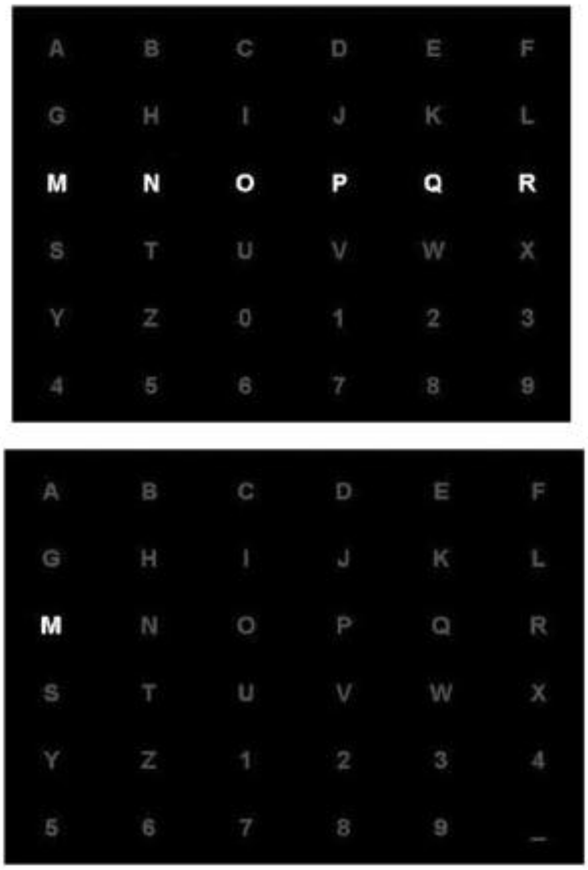

Fig 6: Row/Column Paradigm: row and columns are flashed

Fazli, et al., [22] investigated the Near-Infra Red Spectroscopy (NIRS) which was used to enhance the EEG approach. Noninvasive BCI had been promoted to be used for neuroprosthetics. However, reports on applications with EEG showed a demand for a better accuracy and stability. In this both methods were applied simultaneously in a real- time Sensory Motor Rhythm (SMR)-based BCI paradigm by involving an executed movements as well as motor imagery, and tested how the classification of NIRS data complements the ongoing real-time EEG classification. From experimental results were seen that the simultaneous measurements of NIRS and EEG significantly improved the classification accuracy of motor imagery over 90% of considered subjects and increases performance by 5% on average (pb0:01). Additionally it was found that the EEG and NIRS complement each other in terms of information content and were thus a viable multimodal imaging technique, suitable for BCI.

B. Online single-trial EEG-based brain–computerinterface

A major challenge in BCI research was training subjects. This research aimed to develop an interaction technique which would allow an effective BCI for hand grasping in reality. Hazrati, et al., [23] proposed an online single-trial EEG-based BCI to control hand holding and hand grasping/opening sequence through an interactive virtual reality environment.

This work aims to check whether naïve/untrained subjects can achieve satisfactory results online without offline classifier training. Two classification schemes were utilized: adaptive and static. The adaptive scheme was taken recourse to in the first sessions (days) with feedback to train a classifier and then to use this classifier for further experiments (days) with neither adaptation nor offline calibration.Analgorithmwasappliedto–BCI Competition 2003‖ III data set got by Graz group. The experiment had seven runs of 40 trials each. Evaluation on ten naive subjects showed an average classification accuracy of 75.4% from the first session (day) after about 3 min online training and no offline training, and 81.4% in the second session (day). Average rates in the third and eighth sessions were 79.0% and 84.0%, respectively, through use of earlier calculated classifier in the first sessions, without online training and need for calibration. The results from more than 5000 trials on ten subjects proved that this procedure provided a robust performance over various experiment sessions andsubjects.

Giovanni, et al., [24] undertook a study devoted to classification of four class mental tasks data for a

BCI protocol. MLP Neural Network and Fuzzy C-means analysis were adopted to classify left and right hand movement imagination, mental subtraction operations and mental recitation of a nursery rhyme. Five subjects participated in the experiment in 2 sessions recorded on different days. Various parameters were tried for performance evaluation of two classifiers: accuracy, i.e., percentage of correct classifications, training time and size of training dataset. The results revealed that even when accuracies of both classifiers was the same, the MLP classifier needed a smaller training set to reach them regarding the Fuzzy one. This leads to MLP being preferred for mental tasks classification in BCI protocols. The results through fuzzy logic in task classification on average included 78%correct classifications, peaking at 82%. The classification results showed that both classifiers achieved same average accuracy; but it was seen that MLP neural network needed fewer trials for training purposes, having an advantage in reduced recording sessions which was nearly 8 times lower than Fuzzyanalysis.

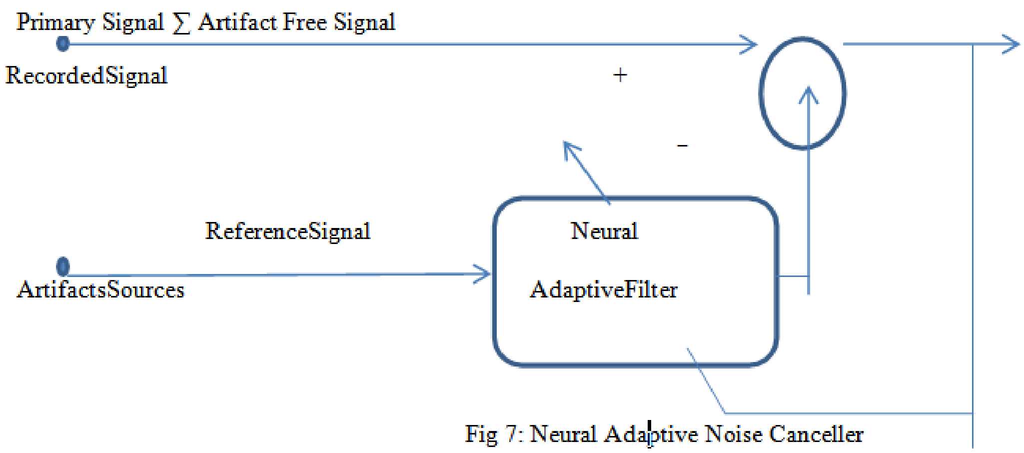

Fig 7: Neural Adaptive Noise Canceller

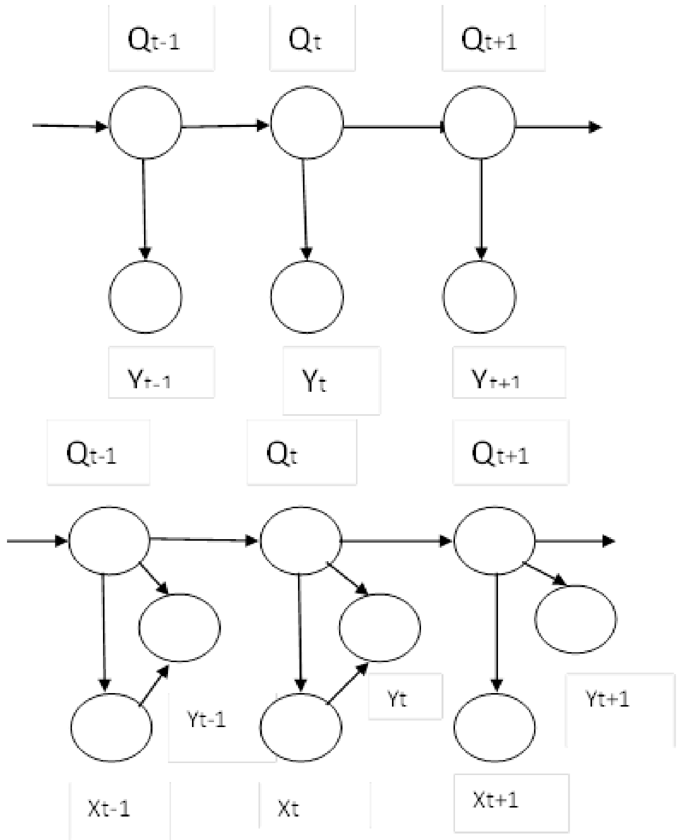

Fig 8: Pictorial model representing the conditional independence properties for HMM and IOHMM

Silvia, et al., [25] contributed to the exploration of the use of Markovian models, specifically, HMMs and its extension - the Input-Output HMMs – to differentiate between three cognitive and motor related mental tasks so that BCI systems founded on an asynchronous protocol could differentiate between three mental tasks for BCI systems using an asynchronous protocol. It was also revealed that IOHMMs outperformed HMMs but that, due to lack of earlier information on state dynamics, no practical advantage was gained through use of these models over static counterparts. In this protocol, the subject followed no fixed scheme but concentrated again and again on a mental task for a random duration. It also switched directly to the next, without going through a resting state. Thus signals associated with every mental task represented a continual sequence of mind events without specific beginning/end from which Markovian models could extract discriminant information on underlyingdynamics.

Hybrid BCI

Amiri, et al., [26] reviewed and discussed about the hybrid BCI in detail. Research teams have studied the features of different data acquisition techniques, brain activity patterns, feature extraction techniques, methods of classifications, and many other aspects of a BCI system. Moreover, conventional BCIs had not become totally applicable, due to lack of high accuracy, reliability, low information transfer rate, and user acceptability. In proposed work, each system was to combine two or more BCI systems with different brain activity patterns or different input signal sources which were called as hybrid BCI and it reduces disadvantages of each conventional BCI system. Hence how to combine BCI systems, its advantages and its disadvantages wereanalyzed.

Savic, et al., [27] presented a study of hybrid BCI for the control of Functional Electrical Stimulation (FES) during grasp rehabilitation. Proposed BCI was operated in two stages sequentially such as: 1. A Steady-State Visual Evoked Potential (SSVEP) which was based method for the selection of one of the three objects for grasping. 2. Event- Related De-synchronization (ERD) which was based on detection of the onset of reach-to-grasp selected object. Adequate stimulation pattern for selected object was determined in first where triggers FES assists the desired grasp in second method. Mean detection accuracies of SSVEP based selection and ERD based detection of the onset of movement for three subjects tested were 98.1% and 100% respectively which could be tested for the control of FES during Functional Electrical Therapy(FET).

Yong, et al., [28] proposed a novel artifact removal algorithm for hybrid BCI systems. The hybrid system combines a self-paced BCI with an eye-tracker to operate a virtual keyboard. The user must gaze at the target for the dwell time to select a letter and then activate BCI by performing a mental task. Unfortunately, EEG signals were often contaminated with artifacts where artifacts change the quality of EEG signals and subsequently degrade the BCI's performance. With semi-simulated EEG signals, the proposed algorithm achieves lower signal distortion in both time and frequency domains. For removing artifacts, the proposed algorithm used the stationary wavelet transform which combined with a new adaptive thresholding mechanism. For real EEG signals, the hybrid BCI system's performance has been evaluated in an online-like manner, i.e., using the continuous data from the last session as in a real-time environment. With real EEG signals, the demonstration for dwell time of 0.0s, the number of false- positives/minute was 2 and the True Positive Rate (TPR) achieved by the proposed algorithm was 44.7%, which was more than 15.0% higher compared to other state-of-the-art artifact handling methods. As dwell time increases to 1.0s, the TPR increases to 73.1%.

Fazel-Rezai, et al., [21] analyzed BCI systems not using EEG. P300 BCI was based on Event Related Potential (ERP), SSVEP, and ERD. Some of the challenges faced when analyzing these signals were bit rate, reliability, usability and flexibility. The solution suggested by the author was to combine these signals into EEG signals to make the hybrid BCI.

Conventional BCIs suffer from the lack of high accuracy, reliability, acceptability from the user and has low transfer rate. Hybrid BCI is a new method which creates more reliable BCI by taking the advantages of each conventional BCI system. It combines two or more BCI systems with different brain activity patterns or different input signal sources to reduce the limitations of individual BCI system. Setare, et al., [26] reviewed various hybrid BCIs and analyzed the possibilities of increasing the accuracy and the information transfer rate. The event- related desynchronization/synchronization (ERD/ERS), SSVEPs, P300 component of event related potentials (ERPs), and slow cortical potentials (SCPs) are generally used EEG patterns in BCI. The two or more patterns can be combined to make hybridBCI.

Savic, et al., [27] combined SSVEP and ERD for creating make a two-stage hybrid BCI system which triggers Functional Electrical Stimulation (FES)system.

During the stage 1, SSVEP was used for selection of objects. To evoke SSVEP, LEDs with 15, 17 and 19 Hz frequencies were used. The EEG acquired from O1, O2, and Oz channels was used by taking Cz as a reference. The object selection task is done on palmar, lateral and precision grasp. To analyze the data Oz channel is taken because SSVEP activity in Oz channel was more noticeable compared to other channels. Butterworth's band pass filters had been used to detect SSVEP signal to separate frequency bands and a threshold for each subject was fixed manually. One among the three grasp options was selected based on SSVEP, and the task which was reaching movement in which ERD-based BCI was used. EEG signals for this task were recorded from the C3 channel. The Cz channel was used as the reference point. Butterworth's band pass filters was used and the detection algorithm uses the real-time mu and beta band-power estimation. The signal was compared with the manual adjusted threshold and a drop under the threshold was considered as a movement command. accuracy was achieved in the SSVEP stage. Using mu and beta bands, and accuracy were achieved, respectively. This study showed that the presented hybrid BCI can be considered as one of the appropriate combinations for FES triggering application.

Yong, et al., [28] proposed an algorithm to remove the artifacts in the hybrid EEG-EOG BCI. The author used stationary wavelet transform and adaptive threshold mechanism.

For the experiments real EEG signals with simulated artefacts (semi-simulated EEG signals) and real EEG signals were used. Results proved that in the semi- simulated EEG signals, signal distortion was decreased and in real EEG signals, the true positive rate was increased by using the proposed algorithm.

Fazli, et al., [33] combined EEG and NIRS measurements simultaneously for ERD-based BCIs. Two blocks of motor execution and 2 blocks of motor imagery were taken for experiments and in all the blocks, both EEG and NIRS were measured simultaneously. The increase in concentration of oxygenated hemoglobins (HbO) and decrease in concentration of deoxygenated hemoglobins (HbR) were measured for each subject using NIRS. The global peak cross-validation accuracy was considered for evaluation of the hybrid BCI. The mean classification accuracies of HbO, HbR, and EEG for executed movement tasks were 71 %,73.3% , and 90.8 %. For motor imagery tasks they were 71.1%, 65%,and 78.2%. The mean classification accuracies of EEG/HbO, EEG/HbR, and EEG/HbO/HbR for executed movement tasks were 92.6%, , 93.2% and 87.4%, and for motor imagery tasks were 83.2

%, , 86.2% and 83.1%,, respectively. It was shown that the combination of EEG and NIRS improved the classification accuracy in both MI and executed movement tasks. But the information transfer rate may decrease.

S. No	**Author**	**Feature Extraction Techniques Used**	**Classification technique**	**Evoked Potential/Spontaneous Potential as input**	**Classification parameter**	**Results**
1	Zhou et al.,(2008)	Bispectrum based feature extraction	LDA classifier, SVM classifier, and NN classifier were adopted to classify a Graz BCI data set.	Graz BCI data Set	Right and Left Motor imagery hand movements	Outperformed the winner of the BCI 2003 competition on same data set
2	Hubert Cecotti and Axel Graser (2009)	feature selection strategy based on salient connections in the first hidden layer of a neural network trained with all the electrodes asinput	MLP NN trained with all electrodes as input	Event Related Potential like P300 waves, data set II from the third BCI competition	Character recognition	The P300 response precision is improved when electrodes are selected under the new strategy.

3	Coyl et al.,(2004)	Four SOFNNs are used for Feature Extraction. Features are derived from the MSE in prediction or the MSY	LDA is used for Classification	Spontaneous Potential mu and beta rhythms	Right and Left Motor imagery hand movements	Classification accuracy rates touched 94% with information transfer rates >10 bits/min.
4	RakenduRao et al., (2005)	ICA and MP. Neural Network classifier was developed with MATLAB 7 neural network toolbox version 4	ICA and MP. Neural Network classifier was developed with MATLAB 7 neural network toolbox version 4 and	EEG Data provided by Colorado State University.	EEG data set recorded during multiplication, letter composing, rotation, and counting	Reduced neural network classification error
5	Barreto et al.,	Welch's periodogram	standard Bayes optimalclassifier	EEG data	EEG data corresponding to Letter, multiplication, visual counting, geometric figure rotation	Could alleviate problems faced by classifier design Classification accuracy > 73%
6	Hazrati et al.,(2010)	Adaptive and static classification schemes and III data set got byGrazgroup	Bayes' classifier using probabalistic neural network	Evoked Potential and Spontaneous Potential (ERD/ERS and Mu rhythm)	controlling hand holding and sequence of hand grasping and opening in an interactive virtual reality environment	Proved that this procedure provided a robust performance over various experiment sessions and subjects. Classification accuracy 84%
7	Giovanni et al.,	NA	MLP Neural Network and Fuzzy C-means analysis, SVM	EEG	Left and right hand movement imagination, mental subtraction operation, mental recitation of a nurseryrhyme	Both classifiers achieved same average accuracy. MLP neural network reduced recording sessions.
8	Silvia et al.,(2003)		HMMs and its extension - the Input-Output	Evoked Potential	imagination of repetitive self-paced left and	IOHMMs outperformed

	(23)		HMMs		right hand movements and mental generation of words starting with a givenletter.	HMMs
9	Fazel-Rezai et al (2012)	NA	NA	NA	ERP, SSVEP, ERD and Hybrid BCI	Suggested that combine two or more patterns to make hybrid BCI.
10	Savic et al (2012)	SSVEP and ERD and ERD-based BCI	NA	NA	NA	Showed that the hybrid BCI can be considered as one of the appropriate combinations for FES triggering application.
11	Yong et al., (2012)	Stationary wavelet transform and adaptive threshold mechanism	NA	NA	NA	Proved that in the semi-simulated EEG signals, signal distortion was decreased and in real EEG signals, the true positive rate wasincreased
12	Fazli et al (2011)	Combined EEG and NIRS measurements simultaneously for ERD-based BCIs.	NA	NA	NA	Improved the classification accuracy in both mutual information (MI) and executed movement tasks.

VI. CONCLUSION

In this survey, different data acquisition methods, activity patterns in the brain, feature extraction and selection methods, different classifiers and some other aspects of a BCI system are analyzed. The acquired signals may suffer from noise and artifacts because of movement of subjects.

Different preprocessing methods, feature extraction, selection methods are available in literature. No single method will suit for all the applications. Based on the application and quality of collected data the preprocessing and classification method should be selected.

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