Advancements of EEG signal pattern recognition in BCI-based Applications: A Review

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Abstract -This paper describes a research approach as well as BCI-based applications with various advancements that are useful for recognition of EEG signal patterns and to assist development of a brain–computer interface (BCI) based on recognition of subject-specific EEG patterns. It also reports the various methods that are used in recognition system. There are various types of componenets used in recognition of EEG signals that are recorded from sensory motor areas during mental imagination of specific task then classified online and used for cursor control. Different methods have been evaluated today for EEG feature extraction and classification that aims to develop methods of analysis, recognition of epileptic EEG signals and the identification of different categories of MI (Motor Imagery) task. This review can be helpful to provide clinical information of patients having epilepsy, Neurological disorders, mental or physical problems. In BCI, if the MI tasks are reliably distinguished through identifying different patterns in EEG data, motor disabled people could communicate with a device by composing sequences of mental task or movements. The various existing experimental result have demonstrated the effectiveness of the methods useful for the identification of MI task. These techniques can assist clinical diagnosis and rehabilitation tasks. Two different issues are integrated together to study MI classification methods having better performance in the result.

Keywords- EEG, MI, AAM, CSP, ERD

I. INTRODUCTION

BCI provide a communication and control pathway to directly translate brain activities into computer control signals, brain computer interface (BCI) has attracted increasing attention in recent years from multiple Scientific and Engineering disciplines as well as from the public [1]. To repaired sensory Motor functions, it appeals primarily to people with severe Motor disabilities. It aims for developing a technical system that can support communication possibilities for patients having severe neuromuscular disabilities and those who are in particular need of gaining reliable control via non muscular devices [2]. The system uses oscillatory Electroencephalogram (EEG) signals, recorded during specific mental activity, as input and provides a control option by its output. The obtained output signals are presently evaluated for different purposes, such as cursor control, selection of letters, words, or control of prosthesis. [3] Brain is the most powerful and complicated organ in the body, the whole working process is not explored until now. To analyze the brain, the simplest and cheapest method is the recording of EEG signals as compared to other well developed techniques like computer tomography scan or functional magnetic resonance imaging and so on. EEG signals are nonlinear as well as non stationary by nature from their origin [4]. Combined neural information transferred from one group of neuron to other produces electric potential recorded over scalp by a non invasive EEG recording technique otherwise, invasive (surgical) techniques are used to monitor any particular area or to record very low potentials [5]. Nowadays, EEG signal processing covers and serves areas that have their major significance in clinical analysis and diagnosis of various brain diseases as well as technological usage, like devices that are operated directly through brain responses (BCI, robotic arm or limb control) [6]. ERP is a very important class of EEG signals, and it is a response of the brain corresponding to any event or task performed, originated at particular area for very short time.ERP characteristics vary task-to-task and also depend upon the subject (person whose EEG is recorded) [7]. Detection of these ERPs is the base idea of BCI. P300 ERP and steady-state visually evoked potentials are the two widely used signals in the BCI research. P300 potentials have been widely investigated in the design of BCI peelers [8]. In, optimal filtering is designed with independent component analysis, which improves the overall results as well as helps in dimension reduction of the EEG data. Source localization with spatial notch filter is proposed [9], which is able to localize the source accurately within the high-noise

environment. Discrete wavelet transform has been applied [10] to improve the EEG signals through decomposition of the noisy EEG signal into several levels to detect noise components in the EEG signal and remove it. Generally, these algorithms are called wavelet de-noising. The problem in conventional static filtering occurs due to the nonlinear nature of EEG and it becomes more complicated due to the overlapping spectrum of noise signals (EMG, ECG, etc.), and the static filters fails to give accurate separations that affects further steps. Recent reports have indicated that pattern visual evoked potential (P-VEP) can be used as a predicator of the success of Occlusion therapy [12]. P-VEP Tests are commonly used ophthalmology to estimate bioelectrical function of the retina and nerve.[13] Current non-invasive BCI systems based on electroencephalographic (EEG) data are divided in three main classes according to the type of neurons mechanisms: 1) Event Related Ssynchronization and De-Synchronization (ERD/ERS) of sensory motor rhythms μ (8-12 Hz) and β (18-25 Hz). This rhythms typically decrease ERD during motor imagery and increase ERS during motor relaxation [14]; 2) P300 peak elicited by a visual oddball paradigm [15]; and 3) Steady-State Visual Evoked Potentials (SSVEP) elicited by a constant flicker at a given frequency [16]. Occlusion Therapy is of crucial importance in providing timely information regarding squint eye in child.

II. Literature Review

Sr. No.	Year	Method	Database	Features	Achieved Success
1.	1994 [17]	Real time Classifier	Real data set with 3 subject	Identification and Recognition possibility	Demonstrated subjects achieved excellent control through the training.
2.	1996 [18]	EEG Signals Classifier	Real data set	recognize a few mental tasks from online EEG signals and have them associated to simple commands	They have demonstrated that some subjects can learn to control their brain activity through appropriate, lengthy training in order to generate fixed EEG patterns that the BCI transforms into external actions
3.	1997 [19]	A Recognition Technique	Real data set	Show the possibility to recognize a few mental tasks from online EEG signals and have them associated to simple commands	Recognize a few mental tasks
4.	1999 [20]	Recognition Technique	Real data set	They demonstrated that some subjects can learn to control their brain activity through appropriate training to generate fixed EEG signal patterns	Showed that EEG patterns are transformed into external actions
5.	June 2000 [21]	Wavelet Transformation Algorithm	Online data using feedback computed with the band power & LVQ approach	A average ERD curves recorded during motor imagery from the left & right sensory motor cortex , ERD time courses are recorded	EEG signals recorded from sensor motor areas during mental -imagination of specific movements are classified on-line & used
6.	June 2000 [22]	Fourier Transform Algorithm	Online data using feedback computed with the band power & LVQ approach	Average ERD curves recorded during motor imagery from the left & right sensory motor cortex , ERD time courses are recorded	EEG signals recorded from sensor motor areas during mental -imagination of specific movements are classified on-line & used
7.	June 2002 [23]	A dedicated s/w was developed for analysis of signals and Neural N/w training LVQ neural networks system	Real data set	Demonstrate the feasibility of the proposed system for real-time pattern recognition of complex signals	A direct relationship between the dimension of the neural networks and their performance was observed.
8	2007 [24]	Wavelet Packet Transform Technique, Genetic Algorithm	data set of BCI Competition 2003 and the results	The network has been testes for EEG signals tat are provided from the results the power of DSNN in processing of noisy nature signals as EEG signals	the power of DSNN in processing of noisy nature signals as EEG
9.	2009 [25]	Linear discriminate algorithm, common space models and Bayesian methods	off-line experimental electroencephalogram (EEG) signals	wavelet coefficient reconstructed by using wavelet transform, AR model power spectral density as the	research provides a new idea for the identification of motor imagery tasks and establishes a substantial theory and

		and linear lgorithm	from the BCI Competition 2003	frequency feature	experimental support for BCI Application. .
10.	2009 [26]	Particle Swarm Optimization (PSO), Frequency Analysis, SVM Technique, Fast Fourier Transform (FFT)	Own database	EEG frequency bands. While touching, human perceives tactile sensation as information	Implement a method for extracting information on the sense of touch based on electroencephalogram (EEG) analysis.
11.	2009 [27]	Power Spectrum Analysis method , the fast Fourier Transform (FFT), high-pass filtering, independent component analysis (ICA)	Audio visual pictures to induce six emotions. The resulting waves were analyzed using the power Spectrum analysis method.	Waves were analyzed using the power spectrum analysis method. Classified human brainwaves according to emotions and compared the results.	From the results, it is determined that there are small differences between emotions, and relative e power values of the emotions are calculated.
12.	2010 [28]	CSP-based spatial filtering, SVM classifier, a new approach by combining two brain signals including Mu/Beta rhythm during motor imagery and P300 potential	Six subjects, five males, one female aged from 22 to 30, attended the online experiment. Two of them had limited prior experience in the 2-D-cursor control system during the system's Development. The other four subjects were naive users.	Linear SVM is used as a classifier for detecting P300	The six subjects successfully carried out 2-D cursor controlwith satisfactory accuracies (>80%). The results attest to the efficacy of obtaining two almost independent control signals by the proposed approach.
13.	2011 [29]	Spatial filters SVM algorithm,	three subjects (two females and one male, 23–27 years old, university students) to participate in our experiment	Applying pattern extraction and classification methods to EEG responses from different time interval, compare the separability of the spatial patterns contained in different ERP components	Pattern classification can objectively evaluate and quantify the between-category differences of the extracted EEG patterns.
14.	2011 [30]	Notch filter, Bandpass filtering technique	the data sets of BCI Competition 2008 - Graz data set A	In each segment, linear correlation coefficients (CCs) were calculated for all possible pairs of channel. evaluated inter-channel connectivity using a hannel-to-channel correlation	Evaluated the temporal patterns of connectivity between EEG channels by the time-varying patterns of the channel-to-channel CCs and the average CC per channel.
15.	July 2012 [31]	FLNN Classifier	Real time database	A novel classification algorithm for a four state BMI design for a wheelchair control using motor imagery	The performance of the four-state BMI is tested with three feature sets. From the result it is observed that the performance of the BMI is better for the FLNN model using MEIG features with an average efficiency of 93%.
16.	Dec 2013 [32]	Continuous Wavelet-Transform Technique, Serial Adaptive method,	EEGs were recorded in six adult WAG/Rij male rats (7–9 months old)	SS-patterns were identified visually in EEG as sequences of 8–14 Hz waves	SS and SWD discussed, accuracy is increased from 71.4% to 87.6% in SS-patterns and from 94.1% to 98.3% in SWD-patterns.

IV. CONCLUSION

Initially, we have studied the basic of BCI and its different applications. This paper presents review on classification techniques that used for recognition of EEG signals pattern. Specifically this paper addressed the effectiveness of variability in the techniques used for classification and recognition of EEG signals pattern and their various application fields. Through this literature review different techniques are practically analyzed for

searching an exact result or finding average percentage that illustrates how much a technique is effective to get a specific conclusion about the EEG signal pattern and other related features that are extracted.

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