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A Review on Analysis of EEG Signal

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Abstract: The electroencephalogram (EEG) popularly known as brain waves represents the electrical activity of the brain. The scalp EEG is an average of the signals generated by various activities of many small zones of the cortical surface beneath the electrodes. An EEG is used to detect problems in the electrical activity of the brain. The pattern of electrical activity is useful for diagnosing a number of conditions that affect the brain. The conditions may be epilepsy, dementia, brain tumor etc. By analyzing the EEG signal we can also compare and differentiate the signals generated by brain for different emotions like happy, sad, anger etc. Recently, numerous research and techniques have been developed for processing, feature extraction and analysis of EEG signals. All these techniques and algorithms have their advantages and limitations. This proposed paper discusses various techniques and transformations proposed earlier in literature for processing and analysis of EEG signals in order to develop more effective and efficient algorithm.

Keywords: EEG, brain waves, feature extraction, analysis.

I. INTRODUCTION

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from scalp [1] .The waveforms recorded reflect the activity of the surface of the brain, the cortex. This activity from the brain structures underneath the cortex. The nerve cells in the brain produce signals that are called action potentials. These action potentials move from one cell to another across a gap called the synapse and special chemicals called neurotransmitters help the signals to move across the gap. Physiological control processes, thought processes and external stimuli generate signals in the corresponding parts of the brain that may be recorded at the scalp using surface electrodes [1]. The brain wave is extracted and the signal undergoes various processes like data acquisition, filtering, feature extraction and then analysis for analyzing the signal in any of the aspect, as illustrated in figure 1 [2]. In data acquisition the recorded signals are converted in the form that can be further processed [2]. Any signal other than that of interest could be termed as noise. These are removed using filters. The EEG is a non stationary signal the feature extraction from the filtered data is done either in time domain or in frequency domain [2]. Ones the feature is extracted the signals are studied and compared with the normal EEG signal. After undergoing the above processes the brain waves can be compared and detected in any of the perspective.

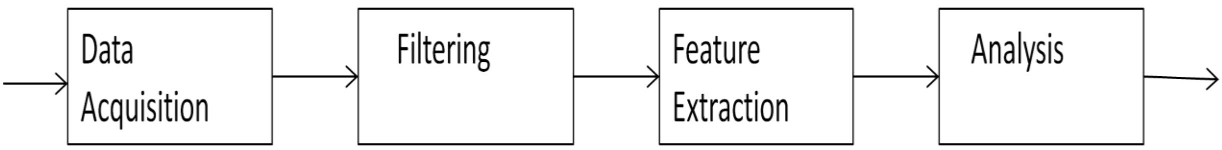

Fig.1 Steps in analysis of EEG signal

II. LITERATURE SURVEY

The literature survey describes various methods for analyzing the EEG signal. A brief description of various processes given by different authors is given below:

Bruno Albert et al. (2016) proposed several methods for automatic processing of EEG data in order to provide a fast and reliable diagnosis of traumatic brain injury (TBI). The development of the automatic TBI diagnosis algorithm is based on advanced EEG signal processing and machine learning techniques. The pre processing step of the algorithm enables the automatic removal of artifacts and noise, avoiding the need for a time consuming manual inspection and removal of data segments. The diagnosis is computed using supervised machine learning based on clinical data. The evaluation of the proposed algorithms has shown it to be fast and reliable with a good generalization performance of the model depression (HD) and low depression (LD) groups did not differ on error rate and reaction time during categorization of gender. The perception of happy faces was accompanied by higher theta synchronization in the LD group than the HD group. In contrast, theta synchronization was higher in the HD than the LD group during perception of angry faces.

Hyuncho Chu et al (2017) investigated a novel seizure precursor based on the attractor state analysis for seizure prediction. Analysis of the transition process from normal to seizure attractor state and investigate a pre cursor phenomenon seen before reaching the seizure attractor state. From the result of an analysis a quantified spectral measure in scalp EEG for seizure prediction is done. Analysis of the transition process from normal to seizure attractor state is done and precursor phenomenon seen before reaching the seizure attractor state. Within scalp EEG, an early warning indicator is defined before an epileptic seizure occurs.

Jean Paul Noel et al (2017) proposed that patients with psychogenic non epileptic event but not patients with epilepsy exhibit changes in multisensory function when compared with healthy controls contrary to our original hypothesis. This study represents the attempt to characterize the multisensory processing abilities of these two patient groups. The patients with PNEE but not patients with epilepsy exhibited enlarged temporal windows within which they bind together audio visual information relative to control subjects. This reduced audio visual acuity may be associated with the cognitive deficits in these individuals and may be a result of changes in networks responsible for the computation of audio visual temporal relations, networks responsible for cognitive biases or a combination of these networks.

Maie Bachmann et al. (2017) proposed a method for detection of depression based on the analysis of single channel short term EEG signal. The accuracy of linear, spectral asymmetry index (SASI) and non linear detrended function analysis (DFA) methods for differentiating depressing and healthy subjects were compared. However this method is not suitable for lengthy EEG recordings.

Mineyuki Tsuda et al. (2014) described a method for analysis and identification of electroencephalography (EEG) about visual stimulation. In this paper improvement and stability of the identification rate of the EEG data has been considered. An innovative method using preprocessing is used. A high dimensional vector consists of the data from four special electrodes to improve the stability is constructed. Various comparative experiments have been implemented and the feasibility and effectiveness have been confirmed.

Mingyang Li et al (2017) proposed a reliable diagnosis method for the epileptic EEG detection based on dual tree complex wavelet transform (DT-CWT). Aiming at requirements that it is desirable to develop a reliable, simple and fast method for the epilepsy detection from EEG signals with non linear features. The reconstruction capability of DT-CWT in epilepsy detection has been explored. Experimental results have indicated that this method has yielded satisfied recognition accuracy of 98.87% combined with SVM classifier which is comparable to the existing methods with the identical data sets. This DT-CWT based technique is able to results in a stable range.

Mingyang Li et al (2017) proposed a method for detecting normal, interictal and epileptical signals using wavelet based envelope analysis (EA) neural network ensemble (NNE). The discrete wavelet transform (DWT) in combination with EA method is developed to extract significant features from the EEG signal. The results are more objective, effective and stable. The discrimination of the features is significantly improved by combining DWT and EA and using as feature extraction. An NNE model is constructed for EEG classification. The proposed algorithm can differentiate among three classes with clinically significant classification accuracy of 98.78%.

Shivnarayan Patidar and Trilochan Panigrahi (2017) explored the ability of the Kraskov entropy of tunable Q wavelet transform (TQWT) based decomposed sub bands for classification of seizure and seizure free EEG signals. The TQWT is a method which helps to develop single feature using Kraskov entropy of TQWT based decomposed sub bands. This single Kraskov entropy based feature has been identified and used as a feature set for classification of seizure and seizure free EEG signals using LS-SVM.

The Kraskov entropy obtained from the last low frequency sub band of third level decomposition has provided better classification accuracy for classifying seizure and seizure free EEG signals. It has been found that the seizure EEG signals have significantly greater value of this feature as compared to that of the seizure free EEG signal.

X. Liu et al (2016) proposed a study to investigate the complexity of EEG signals and distinguish the EEG signals with different rhythms. The EEG time series data used in this study comes from single neural mass model. The model with different parameters produces the EEG signals with different rhythm such as normal EEG signals and epileptiform spikes. The modified permutation entropy extracts the complex features of the normal EEG signal and epileptiform spikes. There are significant differences between them. The signals can be distinguished under different lengths of time series, embedding dimensions and delay times by using the modified permutation entropy. The modified permutation entropy is an effective complexity measure to quantify the EEG signals.

Zhiyong Liu et al (2016) proposed a novel feature extraction method on the multi domain analysis of the EEG. Firstly they conducted the band pass FIR filter to the sleep EEG data. Non stationary and non linear characteristics of EEG into consideration. Fifteen parameters based on multifractal detrended fluctuation analysis (MF-DFA), visibility graph algorithm (VGA), frequency analysis and non linear analyses were extracted. The mean of visibility degree, the mean of distance, the mean of averaged distance and the mean of improved weighted visibility degree algorithm were proposed. By using the LS-VSM classifier ten optimal parameters of the fifteen parameters were determined and the classification of sleep state was successfully completed.

III. CONCLUSION

Electroencephalogram (EEG) opens a window for exploring neural activity and brain functioning. Changes in brain electrical activity occur very quickly and extremely high time resolution is required to determine the precise at which these electrical events take place. By analyzing the EEG signal one can get the knowledge about the kind of signals generated in brain for different emotions, in case of brain injury or in case of any brain disease and compare it from the normal EEG signal. Today's EEG technology can accurately detect brain activity at a resolution of a single millisecond. Careful analysis of the EEG records can provide valuable and improved understanding of the brain electrical mechanisms.

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