



Analysis and Classification of EEG Signal for the Detection of Seizure Using KNN Classifier

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Abstract-The most common neurological malaise that critically vitiates patients' day-to-day survival is Epilepsy. Here we are using a novel approach for the continuous analysis of real time EEG signal. These days, there are many systems helping the neurologists to quickly find noteworthy sections from the extensive signal by automatic seizure detection. Here EEG plays a crucial role in analyzing and classifying the type, severity and curability of the disease. In recent years there has been an increasing interest in applying machine learning methods to the automated detection of neurological disorders in EEG signals. EEG analysis based on machine learning methods has three main steps: pre-processing, feature extraction and classification. The aim of this work is to detect the abnormalities in EEG for the prognosis of seizure with the help of signal processing techniques.

Keywords- Seizure, EEG, KNN classifier.

I. INTRODUCTION

The brain, spinal cord, and nerves make up the nervous system. Together they control all the workings of the body. When something goes wrong with a part of the nervous system, one can have trouble moving, speaking, swallowing, breathing, or learning. There can also be problems with memory, senses, or mood. Such diseases of the nervous system are termed as Neurological disorders. There are more than 600 diseases of the nervous system, such as brain tumours, epilepsy, autism Parkinson's disease and stroke as well as less familiar ones such as front temporal dementia. The most common neurological disorders that affect children are autism, epilepsy and cerebral palsy.

Epilepsy is a group of neurological diseases characterized by epileptic seizures. Epileptic seizures are episodes that can vary from brief and nearly undetectable to long periods of vigorous shaking. In epilepsy, seizures tend to recur, and have

no immediate underlying cause while seizures that occur due to a specific cause are not deemed to represent epilepsy. EEG is an important diagnostic method used to examine epileptic patients and patients with suspicious attack problems.

Electroencephalography (EEG) is widely used in clinical settings to investigate neurophysiology. EEG tests give information about the electrical activity that is happening in your brain at the time the test is carried out. There are several practical advantages of using EEG to study brain function in developmental disorders. Compared with MRI, EEG can be used across a wider range of age groups and developmental abilities to study brain physiology, has a higher relative tolerance for movement, has higher temporal resolution, is more clinically available, and can be used to collect repeated measurements because (compared with positron emission tomography) it is non-invasive.

Resting-state approaches do not require subjects to make a response. This element is particularly promising for studying more severely impaired and/or younger patients who may not be able to



perform tasks accurately because of cognitive, physical, or developmental challenges. With many types of epilepsy, we only have unusual electrical activity in our brain when we are having a seizure. The rest of the time our brain activity is normal. So, if our EEG test doesn't show any unusual activity, it means that there is no epileptic activity in our brain at the time the test is being done. This doesn't rule out the possibility that we have epileptic activity in our brain at other times.

A clear EEG test does not definitely mean that we don't have epilepsy. People with some types of epilepsy have unusual electrical activity in their brain all the time, even when they are not having a seizure. When they have an EEG test, the results can show certain brainwave patterns that doctors recognize. This information is very helpful for doctors when they are making a diagnosis. An example of this is children who have typical absence seizures. EEG is important in the diagnosis of seizure disorders. A high index of suspicion is needed in order to detect non convulsive or minimally convulsive seizures. This is a potentially treatable cause of a CP-look-alike, which is easier to treat when treated early.

The number of research dealing with this issue has increased day by day with the impact of the big developments in the field of electronics and computer. Today, EEG signals are used in many areas such as diagnosis of epilepsy, controlling of anaesthesia stage in surgical operations and determining the depth of anaesthesia, sleep disorders, investigation of sleep psychology and diagnosis of migraine.

II. METHODOLOGY

EEG indicates electrical activity of brain. An EEG analysis literally speaks mapping of brain by localization and similar signal processing methods. Analyses of EEG involve acquisition, cleaning, feature extraction and training. The raw EEG must be visually analyzed carefully for normal typical waveforms, their variants and artifactual segments for deletion prior to further data elaboration, and

considerable expertise is needed to properly identify many of these characteristics. The EEG contains a number of normal waveform variants common among which are the mu rhythm in the central regions, psychomotor variants in the temporal regions, and a variety of different shapes and harmonics of the posterior dominant alpha frequency activity. Intersubject variability is substantial and can be serious confounding factor in EEG research.

There are different methods for the analyses of EEG signals, Fractal Dimension is proposed for investigation of complexity and dynamical changes in the activity of brain. Two methods are investigated for computation of fractal dimension: Higuchi's Fractal Dimension and Katz's Fractal Dimension. A wavelet-chaos-neural network methodology is presented for automated EEG-based diagnosis. Modified multiscale entropy (MMSE) computed on the basis of resting state EEG data can be used as a biomarker of normal brain development. Apart from all these methods, here, I have chosen an effective method for the analysis of EEG signals which is STFT (short time fourier transform). Which gives both time as well as frequency resolution.

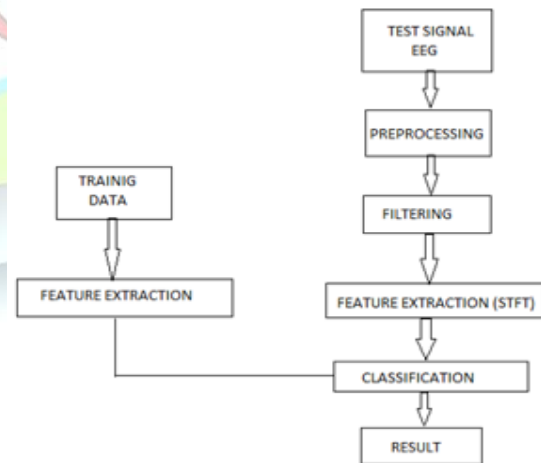


Figure:2.1

Raw EEG signals are collected from 14 different subjects, 7 normal subjects and 7 subjects with



epileptic disorder, the subjects are asked to wear an electrode cap and electrodes are placed on the scalp to take EEG signals, 16 different electrodes are placed over the scalp to take electrical activity in different regions. The electrodes 'Fp1', 'Fp2', 'F7', 'F3', 'F4', 'F8', 'T3', 'C3', 'C4', 'T4', 'T5', 'P3', 'P4', 'T6', 'O1', 'O2' are used according to the International Standard as shown in figure 2.2

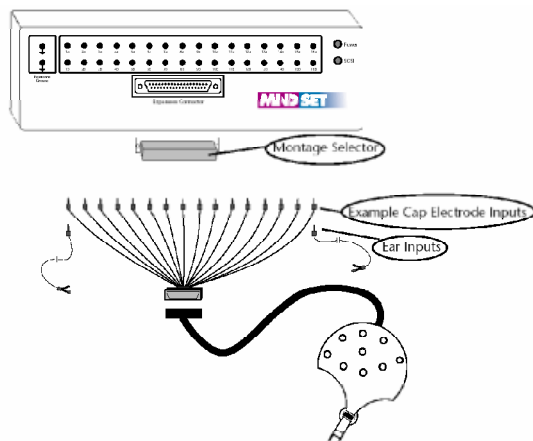


Figure: 2.2

Short time Fourier transform is the primary tool here used for signal processing of EEG signals, the Signal processing methods involve pre-processing of signals which includes processing of training data by removing power frequency and removal of muscular artifacts. Then the pre-processed signals are subjected to segmentation, for the detection of peaks, local peaks and maxima. Then the signals are subjected to feature extraction, where time features are extracted, features of STFT as well as wavelet for multi resolution. Then the signals are classified using a KNN classifier which k nearest neighbour classifier. Finally the input EEG is classified whether it normal or epileptic.

The power noise (50 Hz) is present in the signals obtained from the mindset. A notch filter is used to remove this noise. These muscular artifacts are characterized by high frequencies (20 Hz) and high

amplitudes. These artifacts are prominent in the electrodes 'FP1' and 'FP2'. Figure below shows a typical EEG signal containing an artifact , and a binary signal that identifies the artifacts. The artifacts are identified by differentiating the trials in the frequency domain using the K-Means algorithm. These artifacts can also be detected using the amplitudes as the discriminating factor. But this makes the discrimination too sensitive.

Segmentation using STFT includes dividing the long term signals in to blocks or windows of short time duration. The starting point with STFT is to slice the EEG signals in to short stationary segments; this is performed by multiplying the EEG signals with a sliding window. Segmentation is usually done to detect local and maximum peaks by setting a threshold. In our EEG signal, segmentation is done by sampling the input signal with a sampling frequency of around 1200Hz and the local peaks are identified.

A vast variety of approaches to the extraction of quantitative features from an EEG signal was introduced during more than 70 years of electroencephalography. As for any signal, it seems promising to elaborate a mathematical model of the EEG signal. However, mathematical models and physiological findings linking the EEG to electrical activities of single nerve cells remain problematic, and no single model of EEG dynamics has yet achieved the goal of integrating the wide variety of properties of an observed EEG and single-cell activities. Successful attempts were limited to autoregressive modelling of short EEG segments.

Different methods based on Time Frequency Representations have been considered for the classification of EEG signals. K-NN classifier was finally selected. The classifier is fed with the training data after feature extraction. The classifier out was fixed such that it will visibly distinguish normal and epileptic EEGs. The results indicate that this method is able to extract EEG signals, distinguishing features from the data that could be classified as belonging to



one of the brain abnormality with maximum percentage accuracy.

2.1. KNN ALGORITHM

In pattern recognition, the k-Nearest Neighbours algorithm (or KNN for short) is a nonparametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression. In k-NN classification, the output is a class membership.

A commonly used distance metric for continuous variables is Euclidean distance. For discrete variables, such as for text classification, another metric can be used, such as the overlap metric (or Hamming distance). In the context of gene expression microarray data, for example, k-NN has also been employed with correlation coefficients such as Pearson and Spearman. Often, the classification accuracy of k-NN can be improved significantly if the distance metric is learned with specialized algorithms such as Neighbourhood components analysis.

k-NN is a special case of a variable-bandwidth, kernel density "balloon" estimator with a uniform kernel. The native version of the algorithm is easy to implement by computing the distances from the test example to all stored examples, but it is computationally intensive for large training sets. Using an appropriate nearest neighbor search algorithm makes k-NN computationally tractable even for large data sets. Many nearest neighbor search algorithms have been proposed over the years; these generally seek to reduce the number of distance evaluations actually performed. k-NN has some strong consistency results. As the amount of data approaches infinity, the algorithm is guaranteed to yield an error rate no worse than twice the Bayes error rate (the minimum achievable error rate given the distribution of the data). K-NN is guaranteed to

approach the Bayes error rate for some value of k (where k increases as a function of the number of data points). Various improvements to k-NN are possible by using proximity graphs.

III. RESULTS

The results presented here are the experimental results obtained when raw EEG is subjected to several signal processing methods. This experiment is to set a distinctive difference of epileptic EEG from normal EEG.

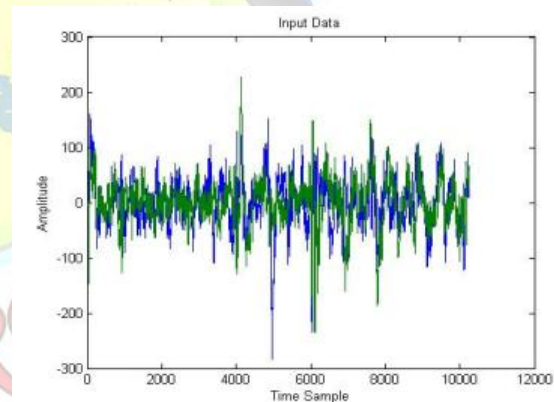


Figure 3.1: Raw EEG Signal

Raw EEG signals are collected from 14 different subjects, 7 normal subjects and 7 subjects with epileptic seizure disorder. Our aim is to classify the given EEG signal by analyzing the given EEG signal through different signal processing methods. Our primary EEG analysis is pre-processing and filtering the given signal, removal of noise and other artifacts. Pre-processing involves removal of power frequency and muscular artifacts. A notch filter is used for filtering the signal. After pre-processing and filtering the signal is subjected to segmentation

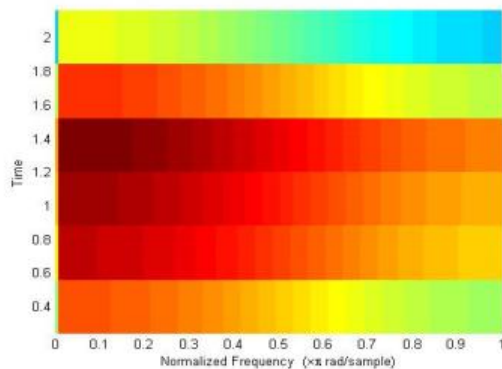


Figure 3.2: STFT Output

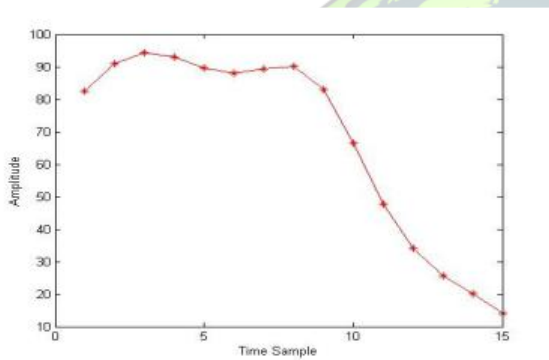


Figure 3.3: Wavelet Transform Output

Feature extraction includes extracting the time as well as frequency features. Short term Fourier transform and wavelet transform are the major techniques we used here for obtaining time as well as frequency resolution. We prefer these techniques to obtain multi resolution. The time features are already obtained by segmentation, the frequency features are analysed in detail by STFT, the segmented signal after subjected to STFT is shown below. [5] discussed about Improved Particle Swarm Optimization. The fuzzy filter based on particle swarm optimization is used to remove the high density image impulse noise, which occur during the transmission, data acquisition and processing.

Wavelet transforms concordinates the time as well as frequency features, so that we get multiresolution. The aim is to approach the EEG signal with a precise

methodology, for that a combination of STFT as well as wavelet transform is chosen.

The feature extracted signal is fed to a classifier, the classifier is trained with a training data, the classifier here we used is a KNN classifier(k nearest neighbour classifier), the classifier classifies the feature extracted data to our final output, that is whether the input signal we have given in the beginning is normal or epileptic. The classifier could give the best result when the signals we used to give at the input side is completely processed without any artifacts, therefore to ensure the best result the training data must also be filtered and feature extracted so that a precise result is obtained.

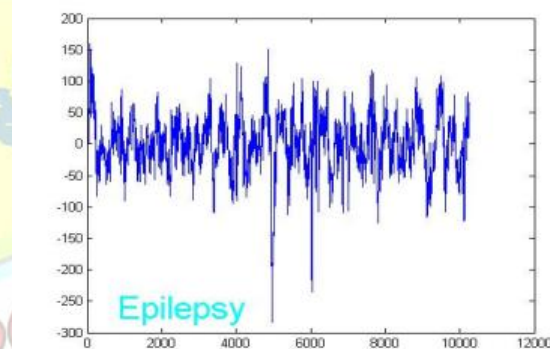


Figure 3.4: Classifier Output (Epileptic EEG)

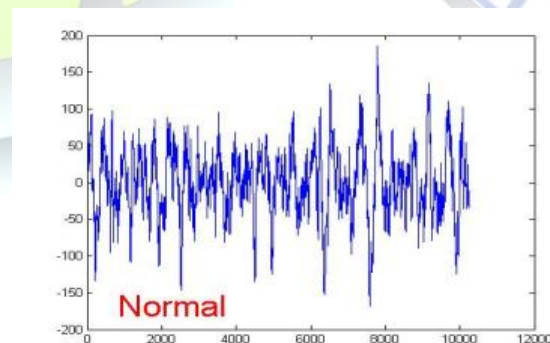


Figure 3.5: Normal EEG

Several other methods to study brain function exist, including functional magnetic



resonance imaging (fMRI), positron emission tomography, magnetoencephalography (MEG), Nuclear magnetic resonance spectroscopy, Electroencephalography, Single-photon emission computed tomography, Near-infrared spectroscopy (NIRS), and Event-related optical signal (EROS). EEG possesses multiple advantages over some of these techniques. EEG has very high temporal resolution, on the order of milliseconds rather than seconds. EEG is commonly recorded at sampling rates between 250 and 2000 Hz in clinical and research settings, but modern EEG data collection systems are capable of recording at sampling rates above 20,000 Hz if desired. MEG and EROS are the only other non-invasive cognitive neuroscience techniques that acquire data at this level of temporal resolution. EEG is relatively tolerant of subject movement, unlike most other neuro imaging techniques. There even exist methods for minimizing, and even eliminating movement artifacts in EEG data.

IV. CONCLUSION

EEG is a powerful tool for tracking brain changes during different phases of life. EEG analyses has got numerous applications. I conclude my work by differentiating normal EEG and epileptic EEG. My work has got many applications in biomedical field and it can be further developed for the analyses of various complex neurological disorders. The work presented here is a part of a larger project, where my goal is to classify EEG signals belonging to a varied set of mental activities in a real time Brain Computer. EEG analyses not only solves identification of epilepsy, but also several other complex nervous disorders such as autism, which gives its visible symptom at the age of three or more. But by proper EEG analyses autism spectrum disorder (ASD) could be identified at the earliest.

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