EEG Based Epileptic Seizure Detection

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***Abstract* — *Epilepsy is common neurological disorders that greatly impair patient daily lives[1]. Traditional epileptic diagnosis relies on lengthy EEG recording that requires the presence of seizure (ictal) activities.EEG has established itself as an important means of identifying and analyzing epileptic seizure activity in humans. The wavelet transform with statistic values to extract features and tested the performance of system by Support Vector Machines are the best cascading technique for EEG signal analysis. The wavelet transform can be use for feature extraction and obtain statistical parameters from the decomposed wavelet coefficients and A Support Vector Machine is used for the classification.*

***Keywords* -**

EEG , support vector machine , entropy , seizure, electroencephalogram , brain, epilepsy.

Introduction-

Epilepsy is a set of neurological disorders characterized by epileptic seizures[1]. Epileptic seizures are episodes that are undetectable to long periods. 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. The causes of epilepsy are unknown, but some people develop epilepsy as the result of brain injury, stroke, brain tumor, drug and alcohol misuse. Epileptic seizures are the result of excessive and abnormal cortical nerve cell activity in the brain[2]. Epilepsy can often be confirmed with an electroencephalogram (EEG) but a normal test does not rule out the disease.

The brain works by transmitting electrical signals between neurons. One way to investigate the electrical activity of the brain is to record scalp potential resulting from brain activity. This method is non-invasive, all measurements are made outside the head and no wounds or scars are made. The recorded signal i.e., potential difference between two positions is called electroencephalogram (EEG). The word has its origins in Greek: (enkephalos) means the brainor literally inside the head and (gramma) means letter or writing. Recording and investigating signals arising from inside the head has been an active field of research for more than 100 years. However, only during the last 50 years or so, with the breakthrough of digital technology, EEG has become a standard method in medical practice. There are also other methods for monitoring the activity of the brain.

EEG signal can be described by its dominant frequency and power. If the signal has very low power it is called suppressed, or in the extreme case when there is no electrical activity.

There is a standard way of attributing Greek letters to different frequency bands[6]. Division of frequencies into these bands was justified by early EEG findings. Nowadays, the most important function of the division is the standardization of EEG vocabulary. Activity lower than 4 Hz is called delta activity. Theta activity is the range of 4 to 8Hz, alpha is 8 to 13Hz, beta is 13 to 30Hz, and activity above 30 Hz is called gamma activity. In addition to describing these general features of the signal, neurologists also look for signs of neurological dysfunctions. Interpreting EEG is a very demanding task. Epileptic seizures form one class of neurological dysfunctions. People with epilepsy have recurrent, unprovoked seizures[6],[7]. However, also people who do not suffer from epilepsy may have seizures. During seizure, there is abnormal electrical activity in the brain. This abnormality is reflected on scalp potentials and hence can be recorded with EEG. Behavioural manifestation can range from subtle finger twitching to convulsions where muscles contract and relax in an uncontrolled fashion, resulting in involuntary body movements.

Literature Survey -

Epilepsy is a fatal condition which is caused as a result of disorder in the nervous system [5]. Epilepsy cause sudden surge in the brain neural activity. The role of electroencephalogram (EEG) signals is important in the diagnosis of epilepsy. In addition, multi-channel EEG signals have much more information than a single channel. But however, traditional recognition algorithms of EEG signals are not so good as compared to multichannel EEG signals [2]. The multichannel EEG signals are used with approximate entropy and statistic values so that we can extract the features. The Support Vector Machines which is also referred as SVMs is used for classification of the EEG signal for epilepsy detection [1], [2]. The other feature also used such as: skewness and kurtosis with a wavelet based approach [1], [4] and Normalized coefficient of variation (NCOV) were extracted from the data [3] .The classification between normal and seizure EEGs was done by using simple linear classifier [3].

In the field of biomedical EEG processing some other approaches are based on detection of seizure by automatic system [4]. Artificial neural network (ANN) is used for the classification without much rely on EEG signal statistical analysis. The Neuro stimulation prior to a seizure may lead to greater efficiency when compared to current treatments which implemented in MATLAB software [1] that alerts epileptic patients for treatment and take preventive measures before the onset of seizure [5]. The EEG signal to extract feature for detecting the seizure rely on frequency band ranging from 3 to 50 Hz.

Background-

The EEG signal is recorded from the scalp by the use of electrodes can be formed as a cap called as electrodes cap. The novel electrode cap is designed to be as easy as possible to put on the patient and to align with anatomical landmarks shown in fig 1.

It can maintain a good electrical contact throughout prolonged recordings. The processing of the EEG can be based on the quality of the signal from the EEG electrodes and the signal processing algorithm. The algorithm should provide an accurate picture of the patients state and address the problem of non-convulsive seizures that are nowadays mostly undetected and therefore untreated.

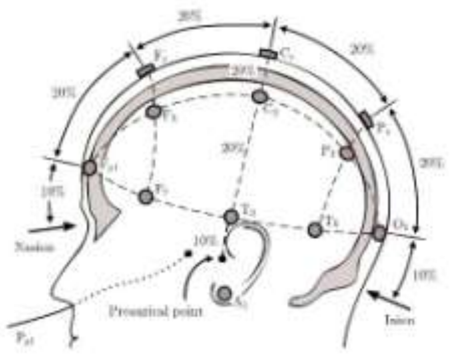

Fig 1: Electrode placement according to the international 10 to 20 system

Data Acquisition-

The All EEG signals were sampled at a sampling rate of 173.61Hz. The data was filtered by a low-pass filter of cut-off frequency 40Hz. An instrumentation amplifier is used to amplify the small signals received from electrodes and requires high signal-to-noise ratio (SNR). The common-mode rejection ratio (CMRR) is usually used to evaluate amplifier instruments, i.e., an amplifier with a higher CMRR reduces the common-mode noise in measurements. The traditional implementation of amplifiers uses a three op-amp configuration, which requires precise matching of the resistors used in the feedback network to achieve a high CMRR. Such matching usually requires expensive laser-trimmed resistors that consume a significant amount of chip area. One technique for overcoming this problem is to use current feedback instrumentation amplifiers, which requires two resistors to adjust the gain, but the resistors are not required to be matched.

Processing-

Fig 2: Block representation of the epilepsy diagnosis detection system.

Filtering-

In order to restrict the EEG signal within the desired frequency band, to remove line noise due to electric supply and to remove stray spikes due to noise, we undertake filtering of the signal. The butterworth bandpass filter with lower and upper cut-off frequencies of 0.35 and 30.5 Hz can be use to eliminate the noise spikes and unwanted signals from other part of body, such as skin statics. The notch filter centered at 50Hz is used to remove the electric supply interference in the EEG signal.

Feature extraction-

There are various features which assembles the EEG signal such as power spectrum representation, decomposition by the wavelet transform. The power spectral features describe energy distribution in the frequency domain and wavelet transform is used to extract the detailed coefficients and approximation coefficients of EEG. The other technique also used such as mean and standard deviation representation of EEG signal amplitude also called as statistic analysis.

FFT transform-

The discrete wavelet transform (DWT) is a versatile signal processing tool that finds many engineering and scientific applications. It has also proven useful in EEG signal analysis. DWT

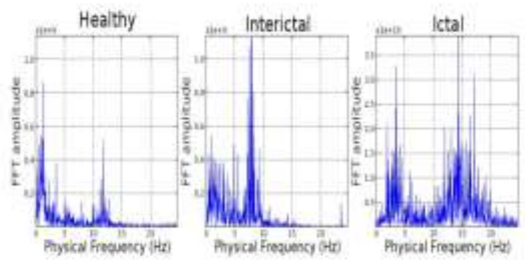

Fig 3: Typical FFT results of 3 EEG segments.

Is a representation of a signal x(t) using an orthonormal basis consisting of a countably infinite set of wavelets. DWT employs two functions, the scaling function and, the wavelet function, which are associated with low- and high-pass filters, respectively. Both of these functions are shifted and scaled as shown below:

$$\Phi_{k,n}(t) = 2^{-k/2}\Phi(2^{-k}t-n) \text{..............................(1)}$$

$$\Psi_{k,n}(t) = 2^{-k/2}\Psi(2^{-k}t-n) \text{..............................(2)}$$

The wavelet representation of a signal x(t) in terms of the scaling and wavelet function is given by

$$x(t) = \sum_{n=-\infty}^{\infty} C_{k0,n}\Phi_{k0,n}(t) + \sum_{k=k_0}^{\infty}\Big(\sum_{n=-\infty}^{\infty}(d_{k,n}\Psi_{k,n}(t))\Big) \text{.....................(3)}$$

where $C_{k0,n}$ is called the approximation co-efficient and $d_{k,n}$ is called the detailed coefficient. The frequency unto which the approximation coefficients are used for representation of the signal is determined by k_0. The decomposition of the signal into the different frequency bands as accomplished by the process detailed above, is simply high- and low-pass filtering of the time domain signal yielding detailed and approximation coefficients respectively. The low pass filters output is further subjected to the same process of high- and low-pass filtering. This is repeated until the number of levels of decomposition desired is reached. The outputs from both the filters are down-sampled at each stage. For this reason, it is to be ensured that the sampling frequency of the signal is at least two times that of the maximum frequency to be analyzed. Selection of suitable wavelet and the number of levels of decomposition is very important in the analysis of signals using DWT. The wavelet can be chosen depending on how smooth the signal is and also on the basis of the amount of computation involved. The number of levels of decomposition is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients.

Wavelet-

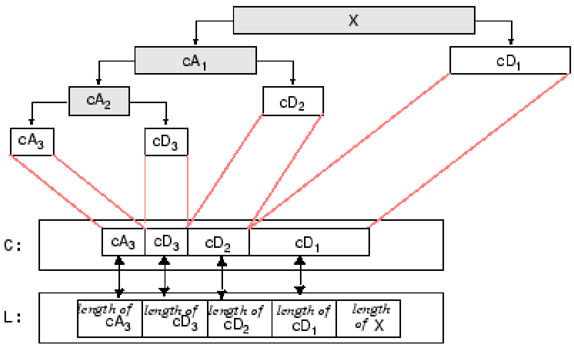

Fig 4: Decomposition of wavelet

Wavedec performs a multilevel one-dimensional wavelet analysis (5.1). using either a specific wavelet (*wname*) or specific wavelet decomposition filters. We are using specific wavelet known as coiflets to decompose the original signal. We are using 512 Hz as sampling frequency to sample the EEG signal so that we get a 5 level of decomposition as in fig 4 and fig 5.

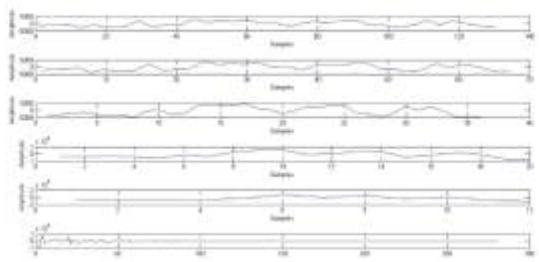

Fig 5: 5 level decomposition

Non-EEG Features-

The earliest measurable sign of some seizures may not be rhythmic EEG activity, but a reflection of the physical sequel of the seizure such as scalp muscle contractions or eye flutter. However these activities are not reliable indicators of a seizure, they are routinely observed outside the seizure state. To a certain whether such routine activity is associated with a seizure, information beyond that within the EEG needs to be incorporated into the detection process. The additional information can be derived using a second physiologic signal whose dynamics are influenced by the presence or absence of a seizure. The second signal and the EEG complement each other if the changes in each signal that suggest the presence of a seizure rarely coincide during non-seizure states, and often coincide at the time of an actual seizure. Patient-specificity remains essential since the manner in which the EEG and the second signal jointly change during the seizure state is patient-specific.

The electrocardiogram (ECG), a non-invasive measure of the electrical activity of the heart, is a good candidate for a complementary signal. It is easy to acquire, and there is significant evidence that seizures for many patients are associated with changes in heart rate.

Feature Vector Classification-

We classify a feature vector as representative of seizure or non-seizure activity using a support vector machine (SVM). Since the seizure and non-seizure classes are often not linearly separable, we generate non-linear decision boundaries using an RBF kernel. Still the SVM does not always enclose the most important data points. As an example, Fig 4 depicts a nonlinear boundary separating seizure (red) and non-seizure (blue) feature vectors extracted from a single EEG channel. The seizure feature vectors form two clusters: one cluster with fewer feature vectors that lies in close proximity to the non-seizure vectors, and a second cluster with a much greater number of vectors far away from the non-seizure vectors. The seizure vectors closest to the non-seizure vectors are associated with the onset of a seizure, and those further away are associated with later stages. In this example, the earliest seizure vector that is correctly classified is the third, which means a delay in declaring seizure onset. It is possible to choose SVM parameters that will force the construction of a more eccentric boundary that encloses the early seizure points, but at the expense of enclosing many more non-seizure points. We train the SVM on seizure vectors computed from the first S seconds of K seizures, and on non-seizure vectors computed from at least 24 hours of non-seizure EEG. A long period of non-seizure EEG is used to ensure that awake, sleep, abnormal and artifact contaminated EEG are included. Selecting the value of S involves a trade-off. A small S focuses the SVM on seizure onset, but also causes the SVM to fail to detect a seizure whenever the onset changes. Increasing S expands the decision boundary and enables the detection of later seizure stages, but increases the detectors false-alarms because the extended boundary encloses more non-seizure vectors.

Support Vector Machines-

The support vector machines (SVMs) map input feature vectors into a high dimensional space to realize a linear classification system[3],[4]. By feeding the algorithm with a set of training data, SVMs can determine an optimal hyper-plane that minimizes the risks.

We first focus on the training problem of a class pair. Giving a training set of instance-label pairs (x, y) and weighting vector w, where x and y denote the input and output domains respectively, assign a penalty to errors and is a slack variable.

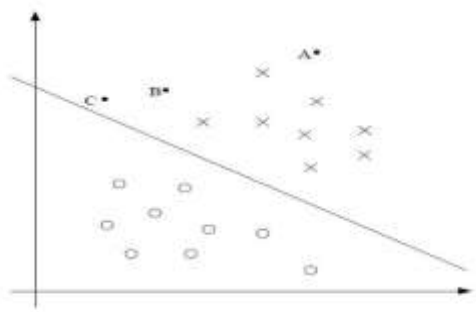

Fig 7: Support Vector Machine classification of feature

Note that it may not be useful to achieve high training accuracy (i.e., classifiers accurately predict training data whose class labels are indeed known). Therefore, a common way is to separate training data by mapping instances into high dimensional domain to build models. After data are mapped into a higher dimensional space, the number of variables becomes very large or even infinite. Diagnose the seizure, the total system will opens up a new area of patient wearable systems for monitoring and analyzing biological signals for seizure detection.

Conclusion-

The main aim of this report was to investigate the development signal processing algorithms for epileptic seizure detection through digital signal processing of EEG signals[4]. It aimed to combine hardware for sensing EEG signals and computer technology to act as the processing hub for monitoring the EEG signals. The project also aimed to carry out small scale investigation by applying statistical analysis with direct evolution of the signal. The wavelet transform with the statistical analysis is the best option for the EEG signal classification and seizure detection[3]. It is easy to understand and implementation of power spectrum analysis is also done prior to the wavelet transform. The power spectrum represents the amplitude spectrum of the EEG signal at particular frequency so it is easy to detect epilepcy.

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