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Analysis of ECG and EEG Signals to Detect Epileptic Seizures

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***Abstract*----Epilepsy is one of the most common neurological disorders, with peak prevalence rates in early childhood and in old age people. It is important to distinguish epilepsy from isolated seizures and cerebral diseases. This epileptic seizure is normally identified from the EEG signal but ECG signal can also be used to detect these seizures. This project intends to develop an algorithm that predicts if a seizure is likely to occur using Electroencephalogram and Electrocardiogram. Features like mean and standard deviation of peak to peak interval, QRS amplitude, QRS time PR interval and QT interval for ECG and spectral power for EEG frequency bands were derived. The power distributions particularly in delta and theta bands were computed to detect the seizures in EEG. Here, both the bio signals are processed simultaneously to predict the extract occurrence of seizure.**

Keywords---- EEG; ECG; Pwave-atrial depolarization; QRS wave-ventricular depolarization; T wave ventricular repolarisation ;Welch power spectrum; seizures

I. INTRODUCTION

Epilepsy is a general term used for a group of disorders that cause disturbances in the electrical signal of the brain. The brain is a highly complex electrical system, powered by roughly many pulses of energy per second. These pulses move back and forth between nerve cells to produce thoughts, feelings, and memories. An epileptic seizure occurs when these energy pulses come much more rapidly for a short time due to an electrical abnormality in the brain This brief electrical surge can happen in just a small area of the brain, or it can affect the whole brain. Diagnosis of epilepsy may be achieved by different examinations, such as positron emission tomography (PET), magnetic resonance imaging (MRI), computed tomography (CT), and Electroencephalogram(EEG). There into, EEG is the most used one with high temporal resolution. In the epileptic EEG, the presence of epileptic activities, such as spikes, sharps and high frequency oscillations confirms epilepsy. An Electrocardiogram (ECG) is another way to diagnose the epilepsy. ECG abnormalities appear to occur more often during seizures and within seizures of longer duration.

II.EXPERIMENTAL PROCEDURE

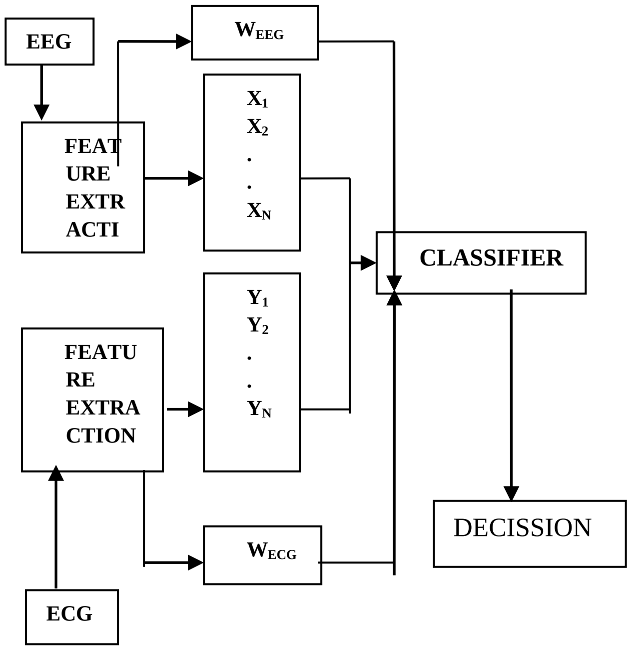

Figure.1. Block Diagram of Epilepsy Detection

The combination of both ECG and EEG is used for seizure detection. Both these signals are capable of identifying seizure from any patient with a minimal false detection rate. The algorithms considered in this study are epoch-based, so each seizure event was rounded to the nearest epoch length. The block diagram of the simulation used in this work is shown in figure.1

A. *EEG and ECG dataset*

The database used in this project was collected at the Children's Hospital Boston, which consists of both EEG and ECG recordings from paediatric subjects and also from young subjects(up to 25 years) with seizures. In this database, recordings were collected from 22 subjects (5 males, ages 322; and 17 females, ages 1.5-19). These signals were sampled at a rate of 256 samples per second with 16-bit resolution. The International 10-20 system for EEG acquisition and one channel ECG was used for these recordings.

III. IMPLEMENTATION

This work mainly consists of two processes namely,

- ECG Analysis
- EEG Analysis

A. ECG Analysis

The algorithm reported in this work utilizes the ECG feature, calculated on a 20 sec (5120 samples) non-overlapping epoch basis. The Mean and S.D of Heart Rate, QRS amplitude, QRS Interval, PR Interval, QT Interval are used in this study.

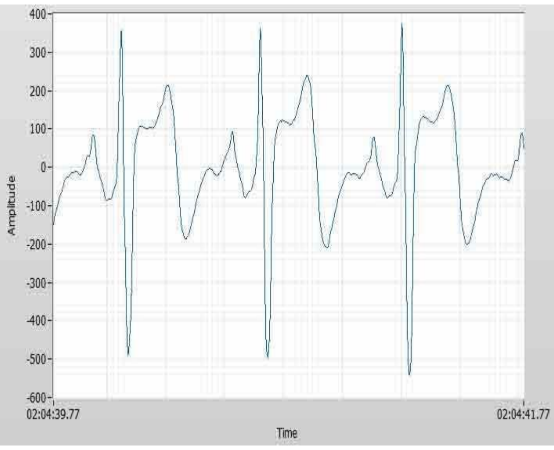

Figure 2 ECG Signal

ECG signal shown in figure 2 was filtered using a band-pass filter (corner frequencies 10 and 25 Hz) to remove baseline wander, power-line noise. The accessibility and the computational simplicity make time domain features the most popular tool for generating outputs.

Mean

The average value, or mean, of a signal x is calculated using the below equation

$$\mu = \frac{1}{N}\sum_{n=0}^{N-1} \mathrm{Xn}$$

It is computed over a time duration of N samples.

Standard Deviation

Standard deviation is equal to the square root of the variance. It is equal to the RMS value for

$$\sigma = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} |Xn - \mu|^2}$$

signals with a zero mean value.

B.EEG Analysis

In this algorithm in order to reduce the complexity signals from four channels namely right frontal FP2-F8 (RF), right temporal T8-P8 (RT), left frontal FP1-F7 (LF) and left temporal T7-P7 (LT) scalp locations are chosen for seizure detection and analysis.

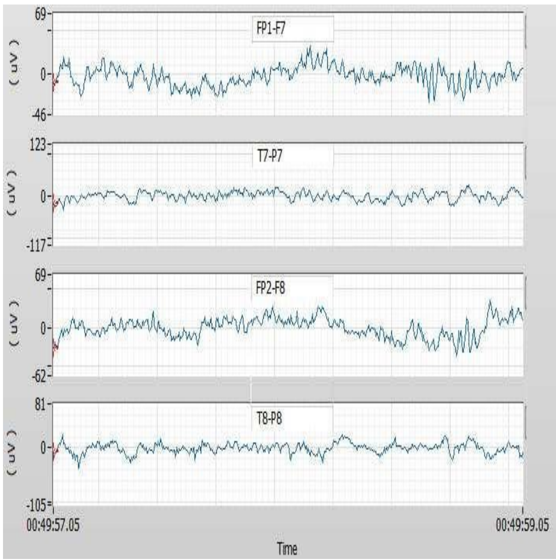

Figure 3 EEG Signal

The EEG signal shown in figure 3 was processed using Daubechies Mother wavelet of order 5 to allow the signal only between 0-32 Hz and also to remove the power-line noise. The frequency domain method is used for EEG analysis. Generally, the rhythmic activity associated with the onset of a seizure is composed of strong frequency components at 2, 5, and 11 Hz. To compute this, the Welch power spectrum estimator was used.

c.Welch Power Spectrum

The Welch method reduces the variance of the periodogram method by averaging. This method first divides a time series into overlapping sub sequences by applying a window to each subsequence and then averaging the periodogram of each subsequence.

$$I_N(e^{jw}) = \frac{1}{N}\left|\sum_{n=0}^{N-1} Xr[m]e^{-jwm}\right|^2$$

d.Neural Network Classifier

In this work, BPN network is employed. Back propagation networks are good classifiers because of their features like robustness, adaptive learning. Here, 26 input nodes, 10 hidden nodes and two output node were used. The MSE Error Goal is set to 0.01, which is sufficient for accurate classification

IV. RESULTS AND DISCUSSION

The features obtained from ECG and EEG were tabulated in the Tables 1, 2 and 3. In all these three tables, the values obtained from the patients under epileptic condition and also under normal conditions were tabulated. In Table1, the mean value of ECG signals from the patients under normal condition and

$$I'_N\left(e^{jw}\right) = \frac{1}{N}\left|\sum_{n=0}^{N-1} X_r[m]e^{-jwn}\right|^2$$

during epilepsy just before the onset of seizure and at the time of seizures were calculated.

In Table2, the standard deviation value of ECG signals from the patients under normal condition and during epilepsy just before the onset of seizure and at the time of seizures were calculated

FEATURE ARTICLE	NORMAL	ABNORMAL	
		PRE SEIZURE	SEIZURE
Heart Rate	81.486	84.042	100.179
QRS Amplitude	1466.497	827.391	951.991
QRS Interval	0.111	0.1	0.097
PR Interval	0.195	0.2	0.148
QT Interval	0.496	0.516	0.409

TABLE I Mean value of ECG

FEATURE ARTICLE	Normal	Abnormal	
		Pre seizure	seizure
Heart rate	3.032	11.05	7.942
QRS Amplitude	97.873	69.09	102.249
QRS Interval	0.011	0.005	0.006
PR Interval	0.012	0.022	0.003
QT Interval	0.012	0.037	0.003

TABLE II Standard Deviation of ECG

In Table3, the Spectral Power calculated from four channels of EEG from the patients under normal condition and during epilepsy just before the onset of seizure and at the time of seizures were calculated.

The calculated features are feed as input to the BPN network from which the occurrence of seizure has been predicted most accurately which is given in figure 4. In this figure, the test data are the features calculated and in the output plot 1 indicates the absence of epilepsy and 2 indicates the presence of epilepsy. Thus in this figure, the occurrence of epilepsy is efficiently predicted.

CHANNEL	BANDS	NORMAL		
			PREICTAL	SEIZURE
T7 - P7	Delta (δ)	232.4	594.01	4599.17
	Theta(Θ)	24.35	39.59	1548.52
	Alpha(α)	11.72	18.18	1439.06
	Beta (β)	4.32	4.94	837.84
FP 1- F7	Delta (δ)	352.49	843.73	5253.54
	Theta(Θ)	31.88	54.12	2109.38
	Alpha(α)	15.13	18.52	1977.46
	Beta (β)	4.26	4.8	1128.86
T8 - P8	Delta (δ)	232.4	594.01	4599.17
	Theta(Θ)	24.35	39.59	1548.52
	Alpha(α)	11.72	18.18	1439.06
	Beta (β)	4.32	4.94	837.84
FP 2- F8	Delta (δ)	257.91	765.91	3936.9
	Theta(Θ)	23.46	51.45	1304.59
	Alpha(α)	10.7	11.66	959.25
	Beta (β)	3.75	2.85	676.98

TABLE III Spectral Power Calculation- four channels

The training performance using the BPN network with mean squared error of 0.01 is shown in figure 5. The features namely mean and standard deviation for ECG signal and power spectrum of the EEG signals were obtained. Finally a BPN classifier is used to classify the feature vectors. The algorithm is evaluated using a large data-set containing ECG and multi-channel EEG. This method provides better performance rates for seizure prediction when compared to methods that uses only the EEG signals.

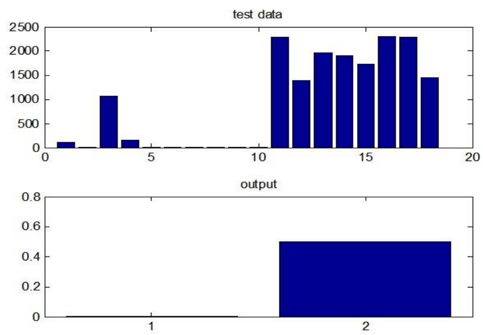

Figure 4 Test data classification using BPN

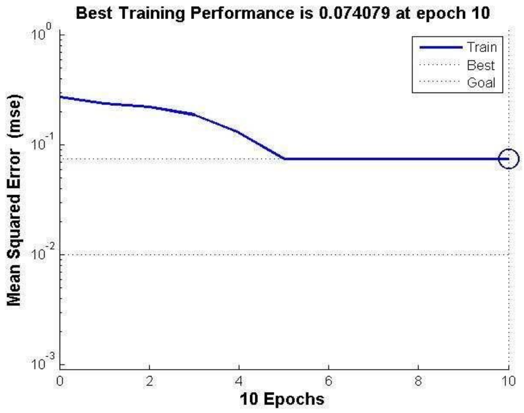

Figure 5 Performance Plot of BPN

V. CONCLUSION

Thereby using this method, as the accuracy rate is higher the false positive rate can be greatly reduced compared to the presently existing methods of which most of them use only the EEG signals for analysing the occurrence of epilepsy This algorithm can be effectively enforced for real time online data processing. Advanced classification methods can be implemented to further increase the performance speed and efficiency of this algorithm.

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