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CLASSIFICATION OF SEIZURE AND NON SEIZURE EEG SIGNAL USING NEURAL NETWORK CLASSIFIER

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***Abstract*—epileptic seizure is the most common disorder of human brain, which is generally detected from electro encephalogram (EEG) signals. Feature extraction and classification is to detect the stages of ictal and inter-ictal signals for treatment and precaution of epileptic patients. In this paper proposes to detect the occurrences of seizure in an epileptic patient from his/her EEG signal, and also perform the accurate timely detection automatically in order to avoid aggressive situation of epileptic seizure using non-invasive EEG signal. The proposed method is to develop a detection system using FPGA techniques to meet the challenges occurred. The implementation results provided that DWT analysis based seizure detection summary of is 15.892ns.The resource utilization for frequency analysis based seizure detection is 1-6%.The resource utilization for seizure detection is 60%.**

***Keywords*—EEG,Epilepsy,Seizure,Discrete Wavelet Transform**

I. INTRODUCTION

Epilepsy is a chronic disorder, the hallmark of which is recurrent, unprovoked seizures. A person is diagnosed with epilepsy if they have two unprovoked seizures (or one unprovoked seizure with the likelihood of more) that were not caused by some known and reversible medical condition like alcohol withdrawal or extremely low blood sugar. The seizures in epilepsy may be related to a brain injury or a family tendency, but often the cause is completely unknown. The word "epilepsy" does not indicate anything about the cause of the person's seizures or their severity. Many people with epilepsy have more than one t and may have other symptoms of neurological problems as well. The data set of EEG signals contains intracranial EEG recordings of 21 patients suffering from medically intractable focal epilepsy. Seizure prediction method is based on a customized phase correlation technique by exploiting spatiotemporal correlation among EEG signals[1].The EEG signals are non-linear and non-stationary signals[2].The prediction process is made by all the data between the end of the previous seizure and the beginning of the next[3].Seizure prediction approach achieves a sensitivity of 75.8%with average false prediction rate of 0.09/h[4].Discrete Wavelet Transform(DWT)as an analysis tool for EEG feature extraction ,which analyse the signal at different frequency bands with different resolutions[5].The effects of pre-processing block including smoothing and normalization of the extracted features[6].The EEG signals are decomposed using empirical decomposition method[7].The EEG epochs were decomposed into five frequency bands using wavelet transform with five scales and three frequency bands at scales 3,4,and 5 were selected for subsequent processing[7-8].The number and quality of available EEG signals are increase that extracts all the available information[9].The single channel EEG data segments are divided into 256 points sliding time epochs with 128 point overlap between adjacent epochs[10].

II.EXISTING WORK

The aim of the existing work is to predict the occurrence of epileptic seizure correctly and timely through an automated way.In the prediction process a preprocessing is applied to remove artifacts,of the raw EEG signals .The differential window is used as a preprocessing ,phase correlation as a feature extraction,LS-SVM as a classification an windowing,regularization as a post-processing..

A. Data Set:

The data set used in the paper was recorded at the epilepsy centre of university hospital of freiburge, Germany. The data set contains intracranial EEG recordings of 21 patients suffering medically intractable focal epilepsy[5].

B. Preprocessing:

Differential window is applied on the raw EEG signals to get more distinguishable signals, applying DW on EEG signals produces more differentiating values to recognize seizure from inter-ictal signals easily compared to the original signals, the signals are visually more distinctive.

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C. Feature Extraction using phase correlation:

The EEG signals is used employing phase correlation, the face information is used to estimate prediction of relative change and phase matched error. The DCT is applied on PME vector is used to determine the energy concentration ratio. The magnitude of the fourier transformed vector indicates to the presence of the frequency component and the phase indicates to the location of the frequency component of the vector. The phase correlation is calculated by applying fast fourier transformation on the reference and current vectors.

D. Classification:

The classifier is used to distinguish the EEG signals they are preictal/ictal and inter-ictal signals, the LS-SVM classifier is the extended version of SVM classifier.

D. Post-processing:

The DW and the phase correlation method attenuate unwanted signals, such as eye blinking, muscle movement etc. Post-processing is applied to accurately predict epileptic seizure on LS-SVM classified signals.

III.PROPOSED METHOD

The aim of this paper is, to detect the occurrence of the seizure in an epileptic patient from his/her EEG signals data. The process of the proposed method is given below.

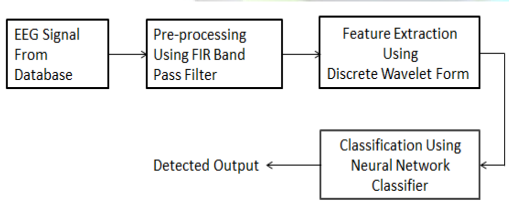

Fig1:schematic representation of overall processing diagram for epiletic seizure detection

Data Set:

The data set used in this paper was recorded at the CHB MIT (children hospital boston Massachusetts institute of technology) physionet bank ATM. It consists of EEG recordings from pediatric subjects with intractable seizures. Recordings were collected from22 subjects.EEG recordings in all channels from seizure start to end(ictal) were considered as “seizure” EEG recordings out of the period of “seizure” were considered as “non-seizure”, the EEG signals were sampled at 256HZ and digitally filtered by the FIR band pass filter.

Preprocessing:

Several preprocessing steps are to be carried out in order to reduce noise and artifacts and a filter is required to eliminate the interference induced by external power mains and equipment. The values of the attributes are standardized by normalizing by max-min approach. Preprocessing step is done using FIR band pass filter. The raw EEG signals have several noises, Noises are removed using FIR band pass filter. Noises are occurred due to interference, equipment malfunction or result from poor electrode contact. FIR band pass filter with the cut off frequency is 0HZ to 128HZ.

$$y(n) = \sum_{i=0}^{n} b_i x(n-i)$$

Where , b_i is the i_{th} coefficient of FIR filter,
Y(n) and X(n) are output and input samples respectively.

Feature Extraction:

To extract a suitable feature set from a epileptic EEG signals is a challenging task as these feature are of prime importance for classification any successful diagnostic system based on classification requires a feature set which is unrelated informative and best representation of the signals. This work has considered statistical features are calculated from each set of every class to achieve representative characteristics of the original signals.one of the features for all the three classes. The features from all the 100 signals of one class are framed together and similar technique is applied for all the three hundred case. thus a final feature set is constituted after using feature ranking method and are arranged according to their clinical significance. This feature set is used as input to the classifier using machine learning algorithm and training and testing sets are generated. These methods reduce the complexity of the system without affecting the classification performance. Most of the classifier results in lower accuracy with raw time-series data as input, which makes feature extraction steps is crucial and important. Trained human can look at the EEG waveforms and determine whether or not a seizure based on closeness to a perfect series. Feature vectors are generated for both seizure and non-seizure activity. Feature vectors can be constructed from empirical mode decomposition which decomposes the EEG signal into amplitude and frequency modulated components, The features parameters include an area under the wave, normalized decay, line length, mean energy, average valley amplitude, peak variation and mean frequency of the components are estimated. The discrete wavelet transform is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules, In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main

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difference from the continuous wavelet transform (or)its implementation for the discrete time series, The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions. The DWT is mainly composed with filters such as high pass and low pass filters. The filter signals are down sampled, The mean value for the acceleration signal are calculated for each second and used as features. The mean value is similar to average rectified value, It can be calculated by taking the average of the absolute value of EEG signal, The mean value of EEG signal,

$$\mu = \frac{1}{N}\sum_{I=0}^{N-1} x_i$$

The variance of each sensor is calculated with a 10 second overlap in order to capture the transient behavior of a seizure and suppress the influence of short jerks,

$$\text{Variance} = \frac{1}{N}\sum_{n=1}^{N} x_n^2$$

.

Classifier:

Artificial neural networks are computing systems made up of large number of simple, highly interconnected processing elements(called nodes (or) artificial neurons)that abstractly emulate the structure and operation of the biological nervous system, learning in ANN is accomplished through special training algorithms developed based on learning rules presumed to mimic the learning mechanisms of biological system. There are many different types and architectures of neural networks varying fundamentally in the way they learn. The neural network relevant to the application being considered(i.e., classification of EEG data)will be employed for designing classification.

A simple two-layer ANN consists only of an input layer containing the input variables to the problem and output layer containing the solution of the problem. This type of network is a satisfactory approximate for linear problems. However, for approximating nonlinear systems, additional intermediate(hidden) processing layers are employed to handle the problems nonlinearity and complexity. Although it depends on complexity of the function or the process being modeled one hidden layer maybe sufficient to map an arbitrary function to any degree of accuracy. Hence three layer architecture ANNS were adopted.

The determination of appropriate number of hidden layers is one of the most critical tasks in neural network design, unlike the input and output layers, one starts with no prior knowledge as to the number of hidden layers. A network with too few hidden nodes would be incapable of differentiating between complex patterns leading to only a linear estimate of the actual trend. In contrast, if the network has too many hidden nodes it will follow the noise in the date due to over-parameterization leading to poor generalization for untrained data with increasing number of hidden layers, training becomes excessively time-consuming. The most popular approach to finding the optimal number of hidden layers is by trial and error.

Training algorithms are an integral part of an ANN model development. An appropriate topology may still fail to give a better model, unless trained by a suitable training algorithm. A good training algorithm will shorten the training time, while achieving a better accuracy. Therefore training process is an important characteristic of the ANNs, whereby representative examples of the knowledge are iteratively presented to the network, so that it can integrate this knowledge within its structure. There are a number of training algorithms used to train a MLPNN and a frequency used one is called the back propagation algorithm, which is based on searching a error surface using gradient descent for points with minimum error, is relatively easy to implement. However back propagation has some problems for many applications. The algorithm is not guaranteed to find the global minimum of the error function, since gradient descent may get stuck in local minima, where it may remain indefinitely. In addition to this, long trimming sessions are often required in order to find an acceptable weight solution, because of the well-known difficulties inherent in gradient descent optimization, Therefore a lot of variations to improve the convergence of the back propagation were proposed.

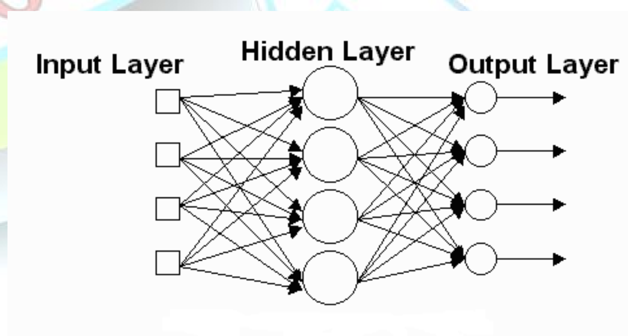

Fig2:simple neural network classifier

Class	Training set	Validation set	Total
Epileptic	102	88	190
Normal	198	112	310
Total	300	200	500

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Table1: Class distributions of the samples in the training and the validation data sets

IV.RESULT AND ANALYSIS

In this paper a seizure detection method is proposed based on the filter using EEG signals from different patients with different brain locations, sex, age, and seizure types. The EEG signals from different brain locations are firstly smothered by fir band pass filter technique. Then the features are extracted using the Discrete Wavelet Transform technique between reference vector and current vector of an EEG signal. A classifier is employed to classify inter-ictal and preictal / ictal signals based on the extracted features. The EEG signals are collected from CHB MIT PHYSIONET BANK ATM. The five types of brain waves are as follows, we choose the alpha waves for better accuracy,

Table2:Types of Brainwaves

Brain waves	Frequency	Output
GAMMA	(25-60)Hz	D13,D12,D11,A14, A15,A12
BETA	(12-25)Hz	D9,A10,A13
ALPHA	(8-12)Hz	A9
THETA	(4-8) Hz	D5
DELTA	(0.5-4)Hz	D8,D7,D6

Alpha waves contain frequencies between 8 and 13 Hz with amplitude less than 10 µV. They are found in normal people who are awake and resetting quietly, their amplitude is highest in the occipital region. when the person is asleep, the alpha waves disappear. When the person is alert and their attention is directed to a specific activity, the alpha waves are replaced by asynchronous waves of higher frequency and lower amplitude.

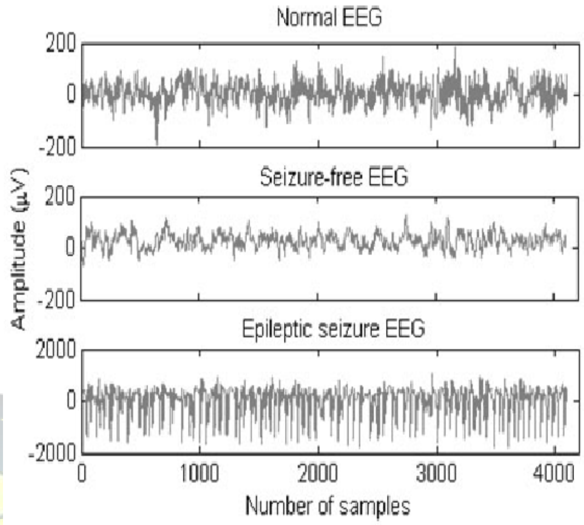

Fig3:Signal Samples

The fig.3 shows the seizure signal, epileptic seizure signal variation from the normal EEG signals. The Pre-processing of EEG signals using the FIR band pass filter, the filter is used to remove the noise artifacts, noises due to eye blinking, muscle movement etc., The noises of the EEG signals are removed and then the signals are used to extracted using the Discrete Wavelet Transform technique. shows in fig,5. A feature set consisting of Shannon entropy, spectral entropy, spectral edge frequency, nonlinear energy, line length, wavelet energy and root mean square EEG amplitude were used to study the epilepsy detection with non seizures shows in fig6. When the wavelet coefficients obtained through sub-band coding were given to artificial neural network (ANN), it could successfully classify 66% normal and 71% abnormal EEGs in this work. It examined the utility of wavelet transform to detect absence seizures (petit mal) which is normally diagnosed by the presence of 3 Hz spike and wave complex. Harmonic and Daubechies order 4 wavelets were found to be more appropriate for wavelet analysis of spike and wave EEG signals[5].developed a wavelet based method for seizure detection, examining how different frequency ranges fluctuate compared to the background. Detection sensitivity reported was close to 90% and the false detections were found to be 0.5 per hour. The number of neurons in the hidden and output layers which use tensing and losing transfer functions are 1and 3, respectively. The error goal for this neural network is set to 0%001. We use60%of the data for training, 20%for validation and 20%for testing. The aver- age training time for each subject is a few seconds achieving 100%accuracy in predicting the task a 60 human subject is about to perform. Our short and successful training phase is due to

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effective processing techniques applied to EEG signals to extract relevant features.

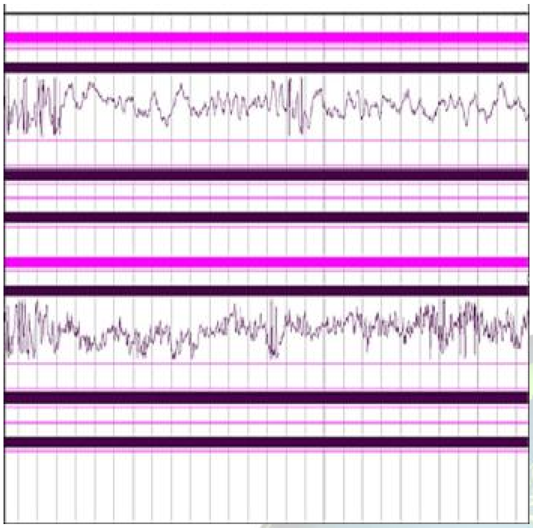

Fig4:Waveform for seizure and normal EEG signal

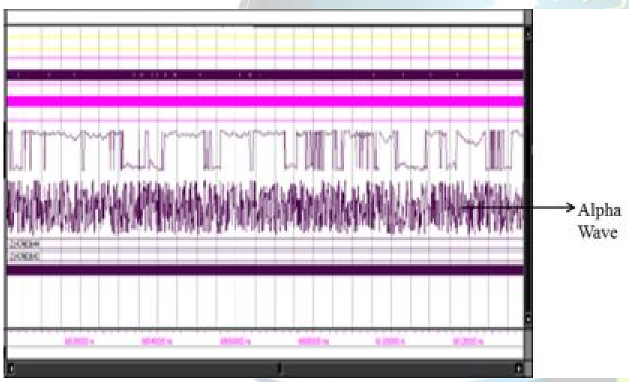

Fig5:Waveform for DWT

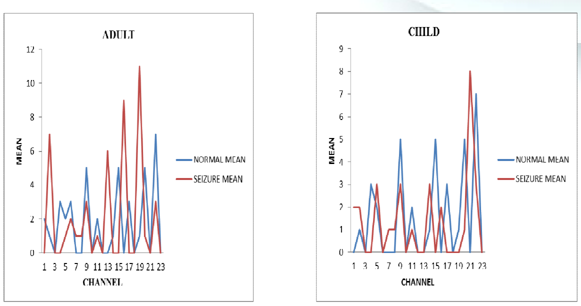

Fig6:Representation of mean values for normal and seizure signals

The mean and variance values are find out by the extracted EEG signals from the epileptic patient.

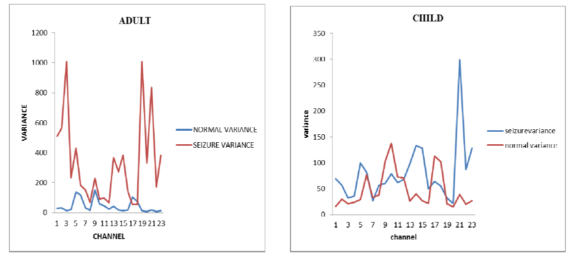

Fig7: Representation of variance values for normal and seizure signals

V.CONCLUSION

In this paper, we have presented a new patient-specific system for the prediction of epileptic seizures from the online analysis of EEG. The system has been designed to be suitable for an implantable realization, and hence is characterized by low computational requirements compatible with the possibility of performing real-time analysis of EEG data. In order to assess the practical behavior of the system, the computational experiments have been performed on the well-known and widely used Freiburg dataset using a subgroup of patients for which data obtained from grid/strip electrodes were available. The results show that the proposed algorithm offers a good combination of sensitivity and specificity, thus making the design of a practical seizure prediction feasible. This paper presents the application method of neural network by signal classification in two classes. The network has one secret layer with 20 neurons, 40 input neurons and one output. If there are a small number of neurons, network may not be able to classify signals correctly. Other way, if there are big numbers of network neurons, network may overload the system. Training set largeness is important too. When using small training set, the network is not able to learn and classify signals correctly. In the future work the neural network will be used to sleep status analysis.

VI.REFERENCES

1.Mohammad zavidparvez and manoranjanpaul "Epileptic seizure prediction by exploiting spatiotemporal relationship of EEG signals using phase correlation",***IEEE Transactions On Neural Systems And Rehabilitation Engineering,*** *Vol. 24, No. 1*, January 2016,pp.158-168.
2.R.Sharma and R.B.Pachori. (2015,Feb)."Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions",***Expert Systems with Applications***,42(3), pp. 1106- 1117.

3.Z. Zhang, Z. Chen, Y. Zhou, S. Du, Y. Zhang, T. Mei, and X. Tian. (2014, Oct).”Construction of rules for seizure prediction based on approximate entropy”.***Clinical Neurophysiology***, 125(10), pp.1959– 1966.

4.S. Li, W. Zhou, Q. Yuan, and Y. Liu. (2013, Oct). “Seizure Prediction Usin Spike Rate of Intracranial EEG”. ***IEEE Transactions on Neural Systems and Rehabilitation Engineering***, 21(6), pp. 880-886.

5.W.Zhou,Y.Liu, Q. Yuan, and X. Li.(2013Apr).”Epileptic Seizure Detection Using Lacunarity and Bayesian Linear Discriminant Analysis in Intracranial EEG”.***IEEE Transactions on Biomedical Engineering***,60(12), pp. 3375-3381.

6.J.Rasekhi, M.R.K.Mollaei, M.Bandarabadi, C.A.Teixeira, and A.Dourado.(2013). “Preprocessing effects of 22 linear univariate features on the performance of seizure prediction methods”. ***Journal of NeuroscienceMethods***, 217, pp. 9–16.

7.V.Bajaj and R.B.Pachori.(2012).”Classification of Seizure and Non- seizure EEG Signals using Empirical Mode Decomposition”,***IEEE Transactions on Information Technology in Biomedicine***, 16(6), pp. 1135-1142.

8.Y.Liu,W. Zhou, Q.Yuan, and S. Chen. (2012).”Automatic Seizure Detection Using Wavelet Transform and SVM in Long-Term Intracranial EEG”.***IEEE Transactions on Neural Systems and Rehabilitation Engineering***, 20(6), pp. 749-755.

9.J.R.Williamson,D.W.Bliss,D.W.Browne,and J.T.Narayanan. (2012, Oct).“Seizure prediction using EEG spatiotemporal correlation structure”.***Epilepsy & Behavior***, 25 (2), pp. 230–238.

10.Y.Tang and D.M.Durand.(2012,Mar).”A tunable support vector machine assembly classifier for epileptic seizure detection”.***Expert Systems with Applications***, 39 (4), pp. 3925–3938.

11.S.Santaniello,S.P.Burns,A.J.Golby,J.M.Singer,W.S.Anderson,and S.V.Sarma.(2011, Dec). “Quickest detection of drug-resistant seizures: An optimal control approach”,***Epilepsy & Behavior***,22(2011), pp.S49-S60.

12.L.Chisci,A.Mavino,G.Perferi,M.Sciandrone,C.Anile,G.Colicchio,and F.Fuggetta.(2010,May). “Real-Time Epileptic Seizure Prediction Using AR Models and Support Vector Machines”, ***IEEE Transactions on Biomedical Engineering***,57(5), pp. 1124-1132.