Australian Journal of Basic and Applied Sciences, 7(12) October 2013, Pages: 174-179

AENSI Journals

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

A Probabilistic Model for Epileptic Seizure Detection in EEG Signal using Time Frequency Analysis and Statistical Pattern

[1]**S.T. Sadish Kumar**, [2]**N. Kasthuri**

[1]*Associate Professor, Department of Electronics and Communication Engineering, Nandha Engineering College, Perundurai, Tamilnadu, Box.638052, India.*
[2]*Professor , Department of Electronics and Communication Engineering, Kongu Engineering College, Perundurai, Tamilnadu, Box.638052, India.*

ARTICLE INFO

Article history:
Received 12 September 2013
Received in revised form 17 *November* 2013
Accepted 20 November 2013
Available online 4 December2013

Key words:
Electroencephalography, Epileptic, Seizure, Wavelet Transform, Probabilistic Model.

ABSTRACT

EEG signals an representative of brain activity towards the electrical signals, which is used to find brain disorders. There are many models have been proposed to find various brain disorders using frequency values of the EEG wave signals. Most of them uses the frequency values of various part of the EEG wave, but lags with the earlier prediction of brain disorders. We propose a new probabilistic model to predict earlier brain disorders using time frequency analysis and statistical pattern. We split the EEG wave into five different portions and convert them into wavelet feature vector i.e energy at different level of decomposition. Each feature vector contains the time and frequency of five different parts of the EEG and age as a feature of the feature vector. We maintain the history of different peoples EEG reading and extracted features in the data base, the proposed model generate statistical pattern from the extracted feature and compute the probability of brain disorder. The proposed model is a learning system, and the feature set will keep on increasing which helps the prediction an accurate one.

To Cite This Article: S.T. Sadish Kumar and N. Kasthuri., A Probabilistic Model for Epileptic Seizure Detection in EEG Signal using Time Frequency Analysis and Statistical Pattern***. Aust. J. Basic & Appl. Sci.,*** *7(12): 174-179, 2013*

INTRODUCTION

The human brain worth of anything and which controls the whole biological system like nerves and muscles. The brain contains of lacks and lacks of neurons and each has its own functionality. Each neuron is capable of conducting electrical signals. Sometimes those neurons will not respond properly for the electrical signal which is called brain disorder. There are many brain disorders and diseases, but the root cause of the disease is the unstable neurons.

The activity of the brain can be measured using various tests available in the medical domain one of them is Electroencephalogram. An electroencephalogram (EEG) is a test to measure the electrical activity of the brain. Brain cells talk to each other by producing tiny electrical signals, called impulses. An EEG helps to measure this activity. The test is done by a EEG specialist in your doctor's office or at a hospital or laboratory. The patient will be asked to lie on your back on a bed or in a reclining chair. Flat metal disks called electrodes are placed all over your scalp. The disks are held in place with a sticky paste. The electrodes are connected by wires to a speaker and recording machine. The recording machine changes the electrical signals into patterns that can be seen on a computer. It looks like a bunch of wavy lines. The patient will need to lie still during the test with your eyes closed because movement can change the results. However, you may be asked to do certain things during the test, such as breathe fast and deeply for several minutes or look at a bright flashing light.

Temporary electrical disturbance of the brain causes epileptic seizures. Sometimes seizures may go unnoticed, depending on their presentation, and sometimes may be confused with other events, such as a stroke, which can also cause falls or migraines. Approximately one in every 100 persons will experience a seizure at some time in their life. Until now, the occurrence of an epileptic seizure is unpredictable and its course of action is little understood. More work is needed for better understanding of the mechanisms causing epileptic disorders. Analysis of the electroencephalograph (EEG) records provides valuable insight into this widespread brain disorder. The detection of epileptic form discharges occurring in the EEG is an important component in the diagnosis of epilepsy.

Corresponding Author: S.T. Sadish Kumar, Associate Professor, Department of Electronics and Communication Engineering, Nandha Engineering College, Perundurai, Tamilnadu, Box. 638052, India.
Tel:+91 99429 03173, E-mail: sadishkumarphd@gmail.com

EEG is used to look at your brain activity. It can help diagnose seizures. It may also be used to diagnose or monitor the following health conditions like Abnormal changes in body chemistry that affect the brain such as Alzheimer's disease, Confusion ,Head injuries , Infections ,Tumors also to evaluate problems with sleep (sleep disorders), Investigate periods of unconsciousness, Monitor the brain during brain surgery.

Brain electrical activity has a certain number of waves per second (frequencies) that are normal for different levels of alertness. For example, brain waves are faster when you are awake and slower when you are sleeping. There are also normal patterns to these waves. Abnormal results on an EEG test may be due to Abnormal bleeding (hemorrhage), abnormal structure in the brain such as a brain tumor, Attention problems, Tissue death due to a blockage in blood flow (cerebral infarction), Drug or alcohol abuse, Head injury, Migraines (in some cases), Seizure disorder (such as epilepsy or convulsions), Sleep disorder (such as narcolepsy) ,Swelling of the brain (encephalitis).

The EEG pattern contains various portion of signals each represent different part of brains activity. A seizure is usually defined as a sudden alteration of behavior due to a temporary change in the electrical functioning of the brain, in particular the outside rim of the brain called the cortex. Seizures can take on many different forms and seizures affect different people in different ways. There are different symptoms at early , during, post condition of seizure.

Wavelets transform a signal processing technique to convert low signals into higher frequency which is used to identify low frequency hidden signals. In our research the wavelet transform method is used to amplify the low frequency signals which are hidden in the seizure. Before splitting the EEG wave, it is applied with wavelet transform and split into different components.

In Analysis of EEG records in an epileptic patient using wavelet transform (Adeli, H., 2003), they discussed the Analysis of EEG records in an epileptic patient using wavelet transform. First they used Discrete Wavelet Transform (DWT) with the Multi-Resolution Analysis (MRA) is applied to decompose EEG signal at resolution levels of the components of the EEG signal (δ, θ, α, β and γ) and the Parseval's theorem are employed to extract the percentage distribution of energy features of the EEG signal at different resolution levels. Second, the neural network (NN) classifies these extracted features to identify the EEGs type according to the percentage distribution of energy features. As EEG signals are non-stationary, the conventional method of frequency analysis is not highly successful in diagnostic classification. In this paper, an algorithm for classification of EEG signal based on WT and PRT has been proposed. DWT with the MRA is applied to decompose EEG signal at resolution levels of the components of the EEG signal and to extract the percentage distribution of energy features of the EEG signal at different resolution levels. The FFNN classifies these different resolution level EEG signals to identify the EEGs type according to the percentage distribution of energy features. The results showed that the proposed classifier has the ability of recognizing and classifying EEG signals efficiently. The most important advantage of the proposed method is the reduction of data size as well indicating and recognizing the main characteristics of signal.

In indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity (Andrzejak, R., 2001), they compare dynamical properties of brain electrical activity from different recording regions and from different physiological and pathological brain states. Using the nonlinear prediction error and an estimate of an effective correlation dimension in combination with the method of iterative amplitude adjusted surrogate data, and analyze sets of electroencephalographic EEG! time series: surface EEG recordings from healthy volunteers with eyes closed and eyes open, and intracranial EEG recordings from epilepsy patients during the seizure free interval from within and from outside the seizure generating area as well as intracranial EEG recordings of epileptic seizures.

In Wavelet transform feature extraction from human PPG, ECG, and EEG signal responses to ELF PEMF exposures (Cvetkovic, D., 2008) they investigate the effects of pulsed electromagnetic field (PEMF) at extremely low frequency (ELF) in response to photoplethysmographic (PPG), electrocardiographic (ECG), electroencephalographic (EEG) activity. The PPG, ECG, EEG signals were decomposed into time-frequency representations using discrete wavelet transform (DWT) and the statistical features like age, sex, weight, location were calculated to depict their distribution. Investigation for any possible electrophysiological activity alterations due to ELF PEMF exposure, was evaluated by the efficiency of DWT as a feature extraction method in representing the signals. As a result, this feature extraction has been justified as a feasible method.

In Statistics over Features: EEG signals analysis, Computers in Biology and Medicine (Elif Derya Übeyli, 2009) Multilayer perceptron neural network (MLPNN) architectures were formulated and used as basis for detection of electroencephalographic changes. Three types of EEG signals (EEG signals recorded from healthy volunteers with eyes open, epilepsy patients in the epileptogenic zone during a seizure-free interval, and epilepsy patients during epileptic seizures) were classified. The selected Lyapunov exponents, wavelet coefficients and the power levels of power spectral density (PSD) values obtained by eigenvector methods of the EEG signals were used as inputs of the MLPNN trained with Levenberg-Marquardt algorithm. The classification results confirmed that the proposed MLPNN has potential in detecting the electroencephalographic changes.

Australian Journal of Basic and Applied Sciences, 7(12) Oct 2013, Pages: 174-179

MATERIALS AND METHODS

The proposed model transforms the low level signals from the EEG wave to high level signals. Each signal consists of various features like time and frequency, those features like energy , time , frequency at different level are extracted using wavelet decomposition methods and constructed feature vectors are analyzed to find out the risk of epileptic seizure and to find out the type of epileptic. Our ultimate focus is to find the probability of permanent unconsciousness called coma. The low frequency features in seizure shows the unconsciousness factor and the low frequency in EEG appears normally while sleeping or at anesthetic. We track the pattern of the patient and find out the chance of recurrence of seizure.

The proposed model consists of the following stages namely Discrete wavelet Transform, Feature Extraction, Seizure Detection, Frequency analysis, Probability Computation and disease prediction. We discuss each of the process in details in the next coming chapters.

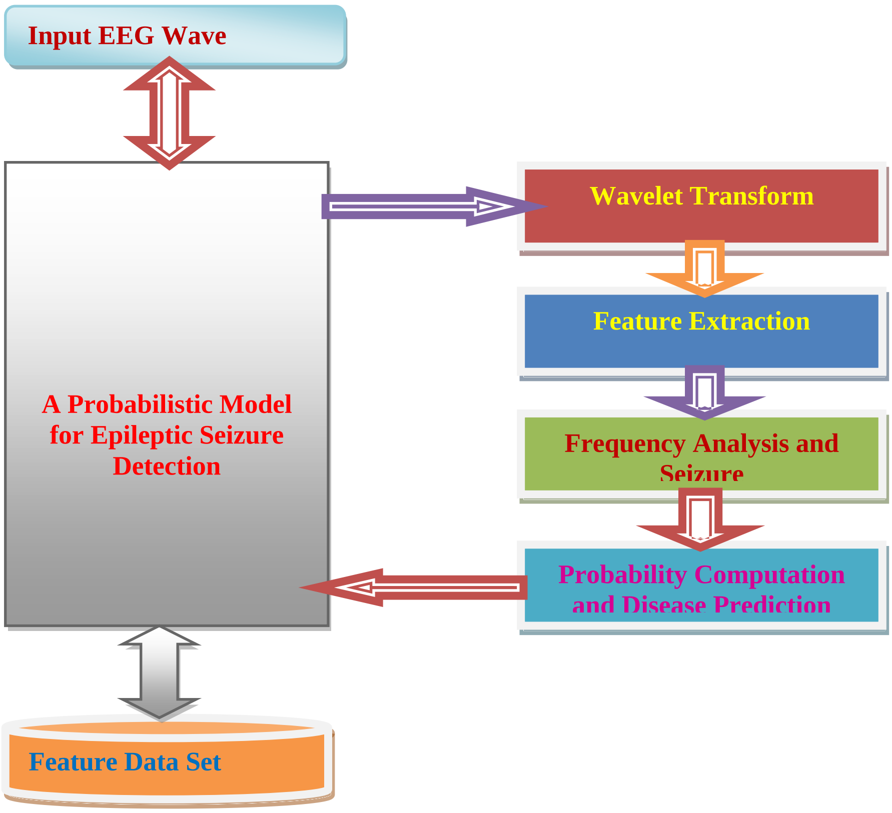

Fig. 1: Proposed System Architecture.

EEG Filtering:

The input EEG signal is applied using wavelet filter and it removes the incomplete and noisy signals from the input signal. The filtered input signal is taken as input for the subsequent processes.

$$WT_{\psi}\{x\}(a,b) = \langle x, \psi_{a,b} \rangle = \int_{\mathbb{R}} x(t)\psi_{a,b}(t)\,dt. \qquad (1)$$

where a, b ∈ x, a = 0 are the scale and translation parameters, respectively, and t is the time.

Wavelet Transform:

The wavelet analysis is applied on the waveform to decompose signals into several frequency bands. We select appropriate wavelet and the number of decomposition levels for the analysis of signals using DWT. The number of decomposition levels 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 necessary for classification of the signal are retained in the wavelet coefficients. Since the EEGs have little useful information

Australian Journal of Basic and Applied Sciences, 7(12) Oct 2013, Pages: 174-179

above frequency 30 Hz of 173.6 Hz, we have selected 5 different bands and frequency ranges and one approximation range.

The following table shows the list of frequency bands we used to decompose the EEG wave into energy features.

Table 1: Different Decomposition levels.

Decomposed Signal	Frequency	Decomposition Level
DS1	64.7-86.8	1
DS2	43.6-64.7	2
DS2	22.5-43.6	3
DS4	11.4-22.5	4
DS5	5.5-11.4	5
DS6	0.0-5.5	6

Feature Extraction:

At this stage the mother wavelet $\Psi(t)$ and the number of decomposition levels N are selected. The energy at different decomposition levels (from 1 to N) is the energy of wavelet coefficients *dj*, *k*, and, in order to simply description, the energy of scaling coefficients *Ck* is defined as the energy at decomposition level N + 1. Thus, the energy at each decomposition level is defined as follows.

$E_j = |d_{j,k}|^2$ where j=decomposition level and k-order of decomposition. Here we used k as 4.

In this work, the energy of each band is used to construct the feature vector v separately. The decomposed wavelet signal at each level of band is used with other features like band E_i , time t, age a are used to construct the feature vector. We

Feature vector $V=\phi\{E_i,t,a\}$.

$E_{i\,-}$ energy at decomposition level i.

Each feature vector from the feature set contains values in the form of v , and will be used further to perform frequency analysis and probability computation.

Algorithm:

Step1: start
Step2: initialize feature set Ψ.
Step3: initialize number of bands N.
Step4: read decomposed results D.
Step5: create feature vector v_i.
Step6: set $v_{i=}\{d_1,d_2,d_3,d_4,d_5,d_6,a,t\}$
Step7: $\Psi=v_i$.
Step8 stop.

Frequency Analysis and Seizure Detection:

The frequency of each band is used to find the presence of seizure. The manual interpretation of EEG may miss the low band values and the low band values are the reason for unconsciousness and coma. We focus on finding those missing values and predict the chance of recurrence and disease probability. All the decomposition levels are used to detect the seizure. The identified seizure is converted to a common patter, which we called statistical pattern which contains information about the seizure and personal details like age, sex, location etc.

Algorithm:

Step1: start
Step2: load feature set : Ψ
Step3: compute Higher energy
    $He = (\sum\{d_1,d_2,d3\})/3$.
Step4: compute lower energy $Le==(\sum\{d_4,d_5,d_6\})/3$.
Step5: if (He<hlimit)
    Seizure =true;
  Else
    If (le <llimit)
        Seizure=true
    End
Step6: statistical pattern sp={age, sex, location, Ψ}
Step6: add sp to trained set.
Step7: stop.

Australian Journal of Basic and Applied Sciences, 7(12) Oct 2013, Pages: 174-179

Probability Computation and Disease Prediction:

The one time occurrence of seizure may or may not be recur in feature. Particularly for pediatric epileptic there is more chance to find second seizure. We compute the probability of recurrence of seizure so that proper treatment could be given. We identify the similar patterns more likely to the input pattern and compute the probability. We use time as a factor, because at the sleeping time the low-level signals are common and even at the time of anesthesia.

Algorithm:

Step1: start
Step2: read trained pattern set E.
Step3: read input feature Ψ, personal details age, sex, location.
Step4: initialize support, count values.
Step4: compute pattern frequency pf.
    For each pattern E_i from E
        If($E_{i(a)}$== $\Psi_{(a)}$)
            Compute pattern distance pd.
            Pd= $\sqrt{}((E_{i(j)-n} - \Psi_{(j)})^2$.
            If(pd<0.5)
                Count =count+1;
            End
        End
    End
    Pf= count/tp.
    Tp- total number of patterns present in E.
Step5: compute probability of recurrence pr.
    Pr = pf×log(tp).
Step6: select the epileptic seizure type.
Step7: send result to user.
Step8: stop.

Results:

The proposed probabilistic epileptic seizure detection model has produced the following results for the input waveform of EEG signal which is obtained different data sets.

The sample waveform of the EEG signal obtained from each dataset is shown in the Fig2.

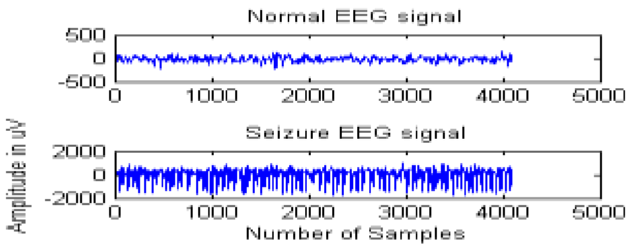

Fig. 2: shows the normal EEG signal and EEG with seizure.

Discussion:

For the evaluation of the proposed system, we have used various data samples of epileptic wave for both adult and pediatric. Our focus is to find the chance of recurrence of seizure in pediatric, because 10-25 lakes of pediatrics have exposed to elliptic seizure in America and they had the chance of recurrence in future.

We have used Matlab simulation tool for the evaluation of the proposed method. The data set used in the paper is publicly available online by Dr. Ralph Andrzejak of the Epilepsy Center at the University of Bonn, Germany. It includes both healthy and epileptic *EEG dataset.* The dataset includes two subsets (denoted as N and S) each containing 100 single-channel EEG segments, each one having 23.6-second duration. The EEG signal available in subset N has been measured in seizure-free intervals, from five patients in the opposite hemisphere of the brain. The Subset S contains the EEG signal during seizure activity period.

From figure 3 , it is clear that the low level frequency values ie band 1,2,3 shows that there is very low brain activity and that feature is used to compute the probability. The computed probability shows that the patient is exposed to epileptic seizure and he has more chance of recurrence.

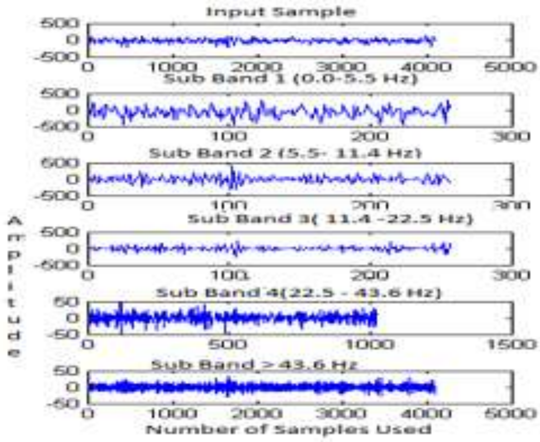

Fig. 3: Shows the various sub bands obtained through our proposed system.

Conclusion:

The probabilistic epileptic seizure detection and prediction has produced good results. The computation of probability has used various features of the EEG wave and age and time factors because the epileptic seizure may recur based on age. The proposed methodology will be useful in case of prediction, with single seizure appearance and could be used to find the chance of seizure in the feature. The pattern mining technique has worked well for our case and produced good results in finding similar patterns of digital signal patterns. The accuracy of prediction is around 97 percent in pediatrics and 85 percent in adult. The proposed method could be tuned by including various factors that affect the epileptic wave and human brain nature.

REFERENCES

Adeli, H., Z. Zhou and N. Dadmehr, 2003. Analysis of EEG records in an epileptic patient using wavelet transform. *Journal of Neuroscience Methods*, 123(1): 69-87.

Andrzejak, R., K. Lehnertz, F. Mormann, C. Rieke, P. David and C. Elger, 2001. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E*, 64(6): 61907.

Cvetkovic, D., E. Ubeyli and I. Cosic, 2008. Wavelet transform feature extraction from human PPG, ECG, and EEG signal responses to ELF PEMF exposures: A pilot study. *Digital Signal Processing*, 18(5): 861-874.

Elif Derya Übeyli, 2009. Statistics over Features: EEG signals analysis‖, Computers in Biology and Medicine, 39(8): 733-741.

Jeybalan, V., A. Samraj, A. Chu Kiong, 2007. Motor Imaginary Signal Classification using Adaptive Recursive Band pass Filter and Adaptive Autoregressive Models for Brain Machine Interface Designs,‖ International Journal of Biological and Medical Sciences, 3(2).

Guler, I. and E. Ubeyli, 2007. Multiclass Support Vector Machines for EEG-Signals Classification. *Information Technology in Biomedicine, IEEE Transactions on*, 11(2): 117-126.

Ghosh-Dastidar, S., H. Adeli, N. Dadmehr, 2007. Mixed-Band Wavelet-Chaos-Neural Network Methodology for Epilepsy and Epileptic Seizure Detection. IEEE Trans Biomed Eng., 54(9): 1545-1551.

Guo, L., D. Rivero, J. Dorado, J.R. Rabuñal, A. Pazos, 2010. Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks. J Neurosci Methods, 191: 101-109.

Guo, L., D. Rivero, J.A. Seoane, A. Pazos, 2009. Classification of EEG signals sing relative wavelet energy and artificial neural networks. GEC'09, Shanghai, China.

He, H., J.A. Starzyk, 2006. A self-organizing learning array system for power quality classification based on wavelet transform. IEEE Transaction On Power Delivery, 21(1): 286-295, ISSN 0885-8977.

Jaffard, S., Y. Meyer, R.D. Ryan, 2001. Wavelets - Tools for Science and Technology, Philadeplhia: SIAM. Klein, S., & Thorne, B.M., 2007. Biological psychology, New York: Worth.

Latka, M., A. Kozik, J. Jernajczyk, B.J. West, W. Jernajczyk, 2005. Wavelet mapping of sleep spindles in young patients with epilepsy. J Physiol Pharmacol., 56(Suppl 4): 15-20.

Lefter, S., O. O'Toole, B. Sweeney, 2010. Epilepsy and driving: new European Union guidelines. Ir Med J., 103(3): 86-88.

Leise, T.L., M.E. Harrington, 2011. Wavelet-based time series analysis of circadian rhythms. J Biol Rhythms., 26(5): 454-463.