Epileptic Seizure Detection Using HWPT based ANFIS Classifier

K.R. Anupriya, T. Sasilatha

Abstract: Epilepsy patients experience challenges in everyday life due to precautions they have to take in order to cope with this situation .When a seizure occurs it might cause injuries or endanger the lives of the patients or others when they are using heavy machinery or driving etc. Prediction of epileptic activities before they occur will enable the patients and caregivers to take appropriate precautions. This paper proposes a novel patient-specific epileptic seizure detection using electroencephalogram (EEG). The proposed method combined both harmonic wavelet packet trans-form (HWPT) and fractal dimension (FD) to extract feature vectors from EEG signals effectively. Finally, the Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to classify the feature vectors obtained from the epileptic electroencephalogram (EEG) signals. The ANFIS classification method combines both neural networks and the fuzzy logic principles together. Finally, the use of less computationally intensive feature extraction techniques facilitates speedy epileptic seizure detection when compared with existing techniques, signifying potential usage in real-time applications.

Keywords: Seizure, Classifier, EEG, ANFIS, HWPT, Fractal Dimension.

I. INTRODUCTION

Epilepsy is a central nervous system (neurological) disorder in which brain activity becomes abnormal, causing seizures or periods of unusual behavior, sensations, and sometimes loss of awareness. Approximately 70 million people were affected by EPILEPSY around the world [1], [2]. This neurological disorder associated with the unprovoked, recurrent epileptic seizures. These seizure is the sudden disturbance of brain electrical activity that signifies the medical signs of hyper-synchronous and excessive hyper-synchronous function of neurons in the brain [2], [3]. Normally, Epilepsy can be diagnosed by using medical examinations, such as and Electroencephalogram (EEG), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Position Emission Tomography (PET), Magneto-Encephalogram (MEG). Among these medical examinations, Electroencephalogram (EEG) is preferred due to high temporal resolution and affordability. An EEG is a medical examination that detects abnormalities in the brain waves, or in the electrical function of brain. However, for a accurate diagnosis and identification epileptic seizures, manual monitoring of EEG is required for several days. This EEG manual monitoring is tedious. Seizure is usually detected by analyzing EEG recordings. The seizure detection process can be made on a single or multichannel basis .Single channel seizure detection requires selecting the channel containing the strongest EEG signal collected from the closest point to the seizure point. A better treatment to seizure detection issue depends on incorporating information from all EEG signals available in seizure detection process through data fusion or multichannel processing techniques .The different methods for seizure detection are Time Domain methods, Frequency Domain methods and Wavelet Domain methods. In time domain seizure detection technique discrete time sequences of EEG epochs are need to be analyzed. This can be done through histograms of the epochs. Runarsson and Sigurdsson et al. proposed a simple time domain seizure detection method based on tracing consecutive peaks and minima in the signal segment at hand and estimating histograms for the two variables: the amplitude difference and time separation between peak values as well as minima [4] Features used for classification are estimated values of histogram bins. Another approach is to compute the signal energy during seizure and non -seizure periods, An even better approach is to estimate the energies of signal sub-bands in order to build a more discriminative feature vector Yoo et al. adopted this approach [5]. Frequency domain techniques can also be used for EEG seizure detection Both the Fourier transform magnitude and phase can be used for this purpose The Author Rana et al. Presented a frequency domain seizure detection approached based on phase slope index(PSI) of multi- channel EEG signals [6]. For time series analysis of physiological signals fractal dimension has been used [7]. Accardo et al. [8] proposed how the fractal dimension (FD) can be used for the characterization of EEG recordings for the various conditions of physiopathological signal. To find the FD of EEG, some of the authors use Higuchi's [9] algorithm. When compared with the Fourier analysis, Higuchi's [9] fractal analysis algorithm provides high temporal resolution. Most of the seizure detection uses machine learning algorithms to classify the extracted features in order to detect seizure. [10]Yuan et al. proposed a new seizure classification algorithm using extreme learning machine [11] with an overall 96.5% accuracy. Shoeb and Guttag [12] also proposed a automated seizure detection method based on the support vector machine (SVM) learning algorithm for classification[13]. Santaniello et al. [14] present a dynamic seizure detection method based on the singular value sequential hidden Markov model estimations in long-term intracranial EEG. In another paper, Acharya et al. [15] evaluated seven different classifiers for the detection of seizure. The Fuzzy classifier provides better accuracy than the other classifiers. Many of these classifiers require estimating initial network parameters for the classification.

Manuscript received January 25, 2019.

K.R. Anupriya, Research Scholar, AMET Deemed to be University. Chennai, Tamilnadu, India.

Dr.T. Sasilatha, Professor and Dean, AMET Deemed to be University. Chennai, Tamilnadu, India.

For example, Artificial Neural Network (ANN) require a active neurons, activation function and no of free parameters and Support vector machine (SVM) requires a hyper plane computation related parameters as the initial network parameters. EEG is classified as intracranial and scalp recordings, based on the electrode placement location. In the intracranial EEG is recording, electrodes placed intrusively under the scalp. In the scalp EEG is recording, the electrodes are placed non-intrusively. So Scalp EEG recordings are widely used[1]. Still, scalp EEG recordings are hypersensitive to noise, that tends to collect artifacts. So, to reduce the false detection artifact reduction algorithms are needed. Though several attempts are made for the seizure detection algorithms using both scalp and intracranial EEG recordings, a reliable, low computed complexity real time automated algorithm is still needed. This study proposes a novel seizure detection method based on harmonic wavelet packet transform (HWPT), fractal dimension (FD) analysis and ANFIS for real time seizure detection using scalp EEG recordings. The combination of harmonic wavelet packet transform (HWPT) and fractal dimension (FD) analysis provide a powerful seizure detector. The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines both the artificial neural networks and fuzzy logic system together. The integration of these two techniques can offer a best result in the seizure detection. In the ANFIS, the system behavior can be described by the membership function parameters, which is trained from the data set. ANFIS study the features from the dataset and according to the error criterion ANFIS can adjust its parameters. The Adaptive Neuro-Fuzzy Inference System (ANFIS) uses hybrid learning method. To optimize the antecedent parameters and the consequent parameters. The classifier integrates the gradient descent technique and the Least Square Estimator (LSE). Based on the sparse features adaptive Neuro-Fuzzy Inference System (ANFIS) can be used to differentiate the epilepsy signal and normal signal.

II. BACKGROUND

Fractal Analysis

Fractal geometry has been used as a describing tool, modeling tool, and analyzing tool for complex objects in nature. Fractal dimension (FD) analysis can be used to detect the self-similar pattern in the complex objects. Artificially generated mathematical objects such as Sierpinski triangle can be used to characterize self similarity properties. Fractal analysis can be used to determine the waveform complexity in the time series analysis. This proposed work proposes a seizure detection algorithm based on the box-counting method, a quick and widely used Fractal Dimension detection algorithm, to detect and analyze the self similar pattern in the EEG waveform.

Harmonic Wavelet Packet Transform

The rhythmic patterns in most seizure related EEG occurs within multiple frequency ranges [1]. Therefore, it is essential to accurately capture these spectral features to increase the sensitivity of seizure detection. Moreover, the non- stationary nature of EEG prompts the use of time-frequency analysis methods to extract such features [1].

Accordingly, this work utilizes a variant of wavelet packet transform known as harmonic wavelet packet transform for feature extraction in EEG. Generic discrete wavelet packet transform methods require recursive calculations for systematic signal decomposition into subsequent levels. In contrast, discrete harmonic wavelet packet decomposition is obtained using harmonic kernels similar to Fourier basis function and does not require recursive calculation to achieve higher frequency resolutions.

ANFIS Architecture

The structure of ANFIS consists of 7 inputs and single output. The 7 inputs represent the different textural features calculated from each image. Each of the training sets forms a fuzzy inference system with 16 fuzzy rules. Each input was given two generalized bell curve membership functions and the output was represented by two linear membership functions. The outputs of the 49 rules are condensed into one single output, representing that system output for that input image. The data set is divided into two categories: training data and testing data. The training data set consists of images from all the four tumor types. These training samples are clustered into four different regions namely white matter, grey matter, cerebrospinal fluid and the abnormal tumor region using the fuzzy C-means (FCM) algorithm. The cluster center of the tumor region for all the four classes are observed and stored. In the testing process, features are extracted and match with the best possible solution.

III. PROPOSED WORK

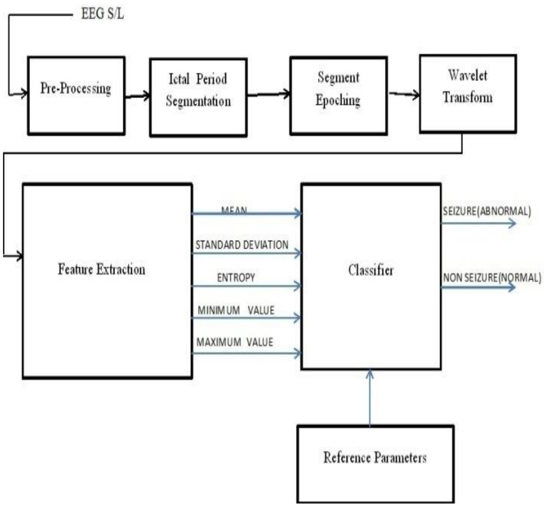

Fig.1: Proposed Block Diagram

The EEG signals obtained from hospitals in .eeg format need to be converted into mat format which is accepted by matlab. The signals are then given to the preprocessing block which removes any artifacts (noises) that may be present in the signal. Median filter is used in this project. After the noise removal ,the signal are then fed to the harmonic wavelet packet decomposition block which decomposes the signal into its constituent frequency sub bands.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The main idea of using the wavelet analysis for EEG seizure detection is extracting discriminating features from appropriate subbands to be used for further classification. The DWT can be implemented with a single level or multiple levels .In this paper DWT method with the wavelet of order 8 was used for decomposing the EEG signals into its constituent subbands.MATLABR2010a was used as the computation tool the coefficients obtained from each frequency subband are then fed as inputs to the ANFIS Classifier block which is a kind of artificial neural network based on Takagi Sugeno Fuzzy Interference system ,since it integrates both neural network and fuzzy logic principles into a single frame work ,It combines the learning capabilities of neural networks with the approximate reasoning of Fuzzy interference systems .ANFIS uses a hybrid algorithm to identify the membership parameters of Takagi- sugeno type fuzzy interference systems. ANFIS systems have been widely used for modeling, optimization, prediction, seizure detection etc. The EEG data were partitioned into two data sets the training data and check data. Two fold cross validation technique is the simplest type of k- fold cross validation .in this method data points are randomly assigned to two sets a0 and a1 which are of equal size. After that the classifier is trained on a0 and tested on a1 and vice versa .This has the added advantage that both the training set and test set are large and each of these can be used for training as well as validation. ANFIS can be considered as a universal classifier.

IV. IMPLEMENTATION AND RESULTS

This section shows the results obtained on implementing the proposed algorithm.

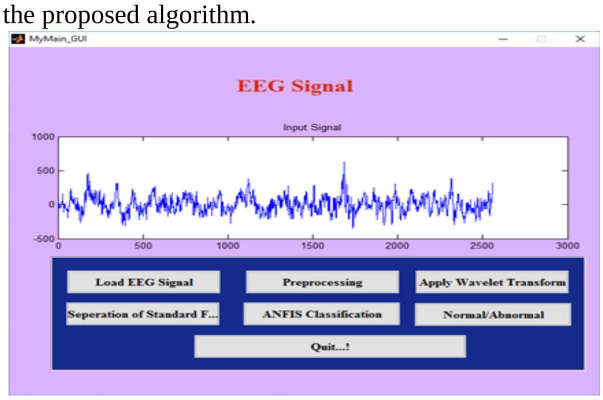

Fig.2: Input EEG Signal

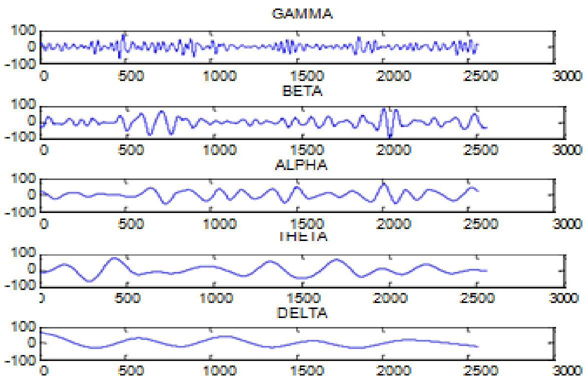

Fig.3: Decomposed Brain Waves (Beta, Alpha, Theta And Delta)

The input signal after preprocessing is decomposed into its constituent subbands using wavelet transform as shown above in fig 3.

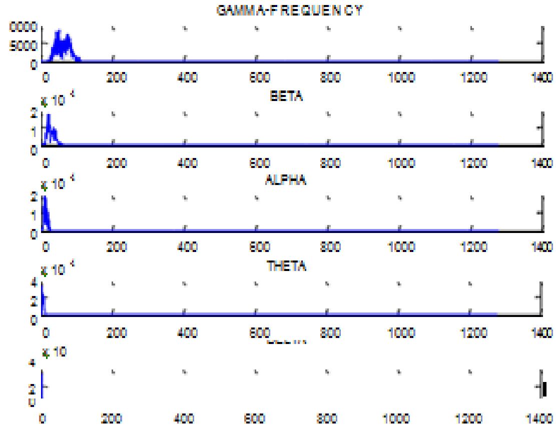

Fig.4: Sub Band Maximal Frequencies

The maximal frequencies obtained from each sub band after removal of zero frequency as shown in fig4

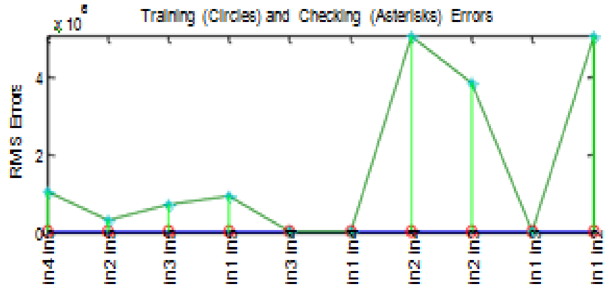

Fig.5: ANFIS OUTPUT: Two input from five Candidates

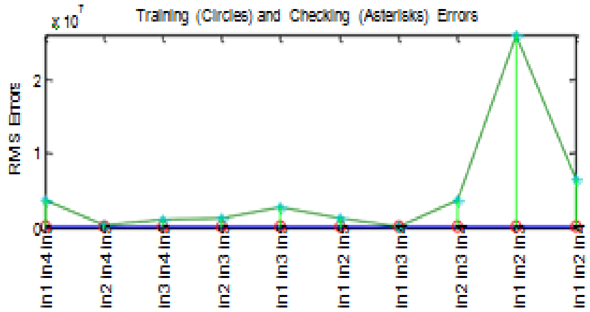

Fig.6: ANFIS output: Three input from five Candidates

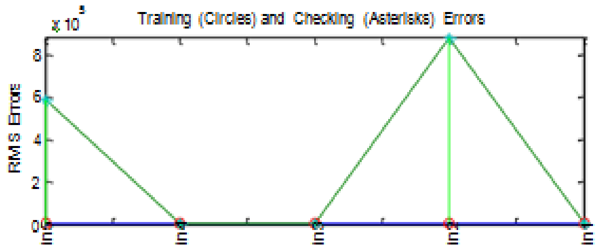

Fig. 7: ANFIS output:One input from five Candidates

The ANFIS Classifier's output shows that the second input in the training dataset shows maximum RMS error and hence can be considered abnormal.

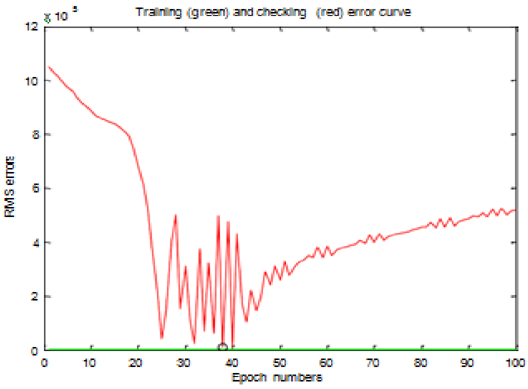

Fig.8: ANFIS Classifier Output

Figure 8 shows that the minimal checking error occurs at the at about epoch 40

V. CONCLUSION

The study shows the importance of seizure detection and prediction algorithm .It also investigates the effectiveness of using wavelet packet transform and ANFIS classifier for EEG signal analysis for seizure detection. More features need to be extracted from the decomposed sub bands in order to obtain better classification. HWPT coefficients could be used as input to other classifiers like support vector machines and their performance can also be analyzed.

REFERENCES

1. A. S. Zandi, M. Javidan, G. A. Dumont, and R. Tafreshi, "Automated real-time epileptic seizure detection in scalp EEG recordings using an algorithm based on wavelet packet transform," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 7, pp. 1639–1651, Jul. 2010.
2. R. B. Yaffe *et al.*, "Physiology of functional and effective networks in epilepsy," *Clin. Neurophysiol.*, vol. 126, no. 2, pp. 227–236, Feb. 2015.
3. J. Gotman, "A few thoughts on 'What is a seizure?"' *Epilepsy Behavior*, vol. 22, pp. S2–S3, Dec. 2011.
4. TP Runarsson, S Sigurdsson, On-line detection of patient specific neonatal seizures using support vector machines and half-wave attribute histograms, inThe International Conference on Computational Intelligence for Modeling, Control and Automation, and *International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA- IAWTIC) (Vienna), pp. 673–677. 28–30 Nov 2005.*
5. JYoo, L Yan, D El-Damak, MA Bin Altaf, AH Shoeb, AP Chandrakasan, An 8 channel scalable EEG acquisition SoC with patient-specific seizure classification and recording processor. *IEEE J. Solid State Circuits 48(1), 214–228 (2013)*
6. PRana, J Lipor, H Lee, WV Drongelen, MH Kohrman, BV Veen, Seizuredetection using the phase-slope index and multichannel ECoG. *IEEE Trans.Biomed. Eng. 59(4), 1125– 1134 (2012)*
7. M. J. Katz and E. B. George, "Fractals and the analysis of growth paths,"*Bull. Math. Biol.*, vol. 47, no. 2, pp. 273–286, Jan. 1985.
8. A. Accardo, M. Affinito, M. Carrozzi, and F. Bouquet, "Use of the fractal dimension for the analysis of electroencephalographic time series," *Biological*, vol. 77, no. 5, pp. 339–350, Nov. 1997.
9. T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," *Phys. D, Nonlinear Phenomena*, vol. 31, no. 2, pp. 277–283, Jun. 1988.
10. Q. Yuan, W. Zhou, S. Li, and D. Cai, "Epileptic EEG classification based on extreme learning machine and nonlinear features," *Epilepsy Res.*, vol. 96, nos. 1–2, pp. 29–38, Sep. 2011.
11. R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite- dimensional structures in time series of brain electrical activity: Depen- dence on recording region and brain state," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 64, no. 6, p. 061907, Nov. 2001.
12. A. Shoeb and J. Guttag, "Application of machine learning to epileptic seizure detection," in *Proc. 27th Int. Conf. Mach. Learn. (ICML)*, 2010, pp. 975–982.
13. A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic sig- nals," *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000.
14. S. Santaniello, S. P. Burns, A. J. Golby, J. M. Singer, W. S. Anderson, and S. V. Sarma, "Quickest detection of drug-resistant seizures: An opti- mal control approach," *Epilepsy Behavior*, vol. 22, pp. S49–S60, Dec. 2011.
15. U. R. Acharya, F. Molinari, S. V. Sree, S. Chattopadhyay, K.-H. Ng, and J. S. Suri, "Automated diagnosis of epileptic EEG using entropies," *Biomed. Signal Process. Control*, vol. 7, no. 4, pp. 401–408, Jul. 2012.