INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

IJARIIT

ISSN: 2454-132X

Impact factor: 4.295

(Volume3, Issue3)

Available online at www.ijariit.com

Automatic Diagnosis of Epilepsy Using Electroencephalogram (EEG) Signal Analysis

M. V Satya Sai Chandra
National Institute Of Technology, Calicut
malyalasatyasaichandra@gmail.com

Dr. Paul K. Joseph
National Institute Of Technology, Calicut
paul@nitc.ac.in

Dr. Thasneem Fathima
MES College of Engineering, Kuttippuram
thasneemzaman1@gmail.com

Abstract: Epilepsy is a very common neurological disorder. Electroencephalogram (EEG) is the major diagnostic tool used for analyzing the human epileptic seizure activity and there is a strong need of an efficient automatic seizure detection using it to ease the diagnosis. This work aims at an automatic system for diagnosis of epilepsy. Here we extract some features like fractal dimensions, sample entropy, Lyapunov exponent, etc of both normal and epileptic EEG signals. These feature values are used as inputs to train classifiers like artificial neural networks, support vector machines, probabilistic neural networks etc., after the training we test the classifier with test EEG data.

Keywords: Electroencephalogram, Fractal Dimensions, Lyapunov Exponent, Support Vector Machine, Neural Networks

1. INTRODUCTION

Epilepsy is a very popular and common disorder in the neurological system. Almost 3 million people in the United States of America are affected and about 50 million people over the world are affected by this disease. About 12% of the world's population have the impact and presence of epilepsy which is more and more in old people. Epilepsy is characterized by sudden repetitive and brief disordering of behaviour. A person suffering from epilepsy experiences constantly occurring abnormal upsurges of the electrical activity of the brain. Epilepsy can be indexed by these constantly recurring upsurges called as seizures.

Neuro physicians find it a bit difficult to analyze EEG manually, primarily because of its randomness and non-periodic nature especially under occurrence of epilepsy. This work aims at an automatic system which could diagnose Epilepsy so that it can be used as an assistive device for physicians. In order to accomplish the objective of this work firstly we take EEG data of both normal and epileptic patients. After that, some statistical features are extracted which are nothing but a qualitative representation of the signal. The obtained feature values will be fed as input to a classifier. This classifier is trained using these input feature values corresponding to both normal person and epileptic person EEG signals. This classifier is then tested with test EEG signals to see its performance.

2. MATERIALS AND METHODS

2.1 Data Used

The data used for the analysis was provided by the University of Bonn, Germany for research purposes. The complete set of data consists of five series (Denoted A - E) containing each 100 EEG segments of a single channel. Sets A and B consisted of segments extracted from Surface EEG recordings were performed using a standard 10-20 electrodes positioning system. Set A was recorded in a daytime wake state and set B was made in the same state with closed eyes. Set C, D, and E were taken by patients with epilepsy. Set C and D that contains only activity measured during free seizure intervals and Set It was taken from all the electrodes indicated and convulsive activity only content. The data was sampled 173 Hz and each data set having a length of 23 seconds has 4096 samples. In this document, we focus only on the entire set of data A and E that are set for normal and epileptic person respectively

2.2 Feature Extraction

Every disease is characterized by some symptoms. Based on some particular symptoms only a physician can conclude the specific disease to start treatment. Here we correlate the symptoms to features which are nothing but some method of time series analysis of the EEG data. Various features can be extracted from EEG signal. Here we are mainly concerned with following features.

Hurst Exponent

Hurst exponent is the measure of the smoothness of a time series. The long range dependence presence or absence in the time series is also investigated using this feature. As said earlier to measure smoothness we do rescaled range(R/S) analysis and take the rescaled range of the time series and observe its asymptotic behaviour. Hurst Exponent value lies in between 0 and 1. Generally, a value between 0 and 0.5 indicates chaotic behaviour in the time series and a value between 0.5 and 1 indicate normalcy. The definition of Hurst exponent HE is as follows,

$$HE = \frac{\log(\frac{R}{S})}{\log(\tau)} \qquad (2.1)$$

Where the $\boldsymbol{\tau}$the duration of data samples and R/S is is the corresponding value of rescaled range.

Katz fractal dimension

Katz's Fractal Dimension calculation is a bit slow and easy to carry on as we analyse the same time series without creating a new time series. The Fractal Dimension of a curve is defined as follows

$$D = \frac{\log_{10}(\mathrm{N})}{\log_{10}(r)} \qquad (2.2)$$

N is the length of the curve which is evaluated by adding distances between successive points. *r* is the distance between the initial point of the sequence and the farthest point of the sequence. This can be found out by maximizing the distance function between the initial point and some arbitrary point *i* in the series.

Sample Entropy (SampEn)

Sample Entropy is a useful tool for investigating the dynamics of signal like heart rate, EEG, and other time series. Sample entropy is the negative natural logarithm of an estimate of the conditional probability that subseries (epoch) of length *m* that matches pointwise within a tolerance or similarity *r* also match for the next point. It measures the randomness of a physiological signal and is independent of the pattern length. If SampEn value of one dataset is higher than the other for a given pattern length (*m*) and similarity criterion (*r*) then it remains higher for all the different values of *m* and *r* . The high value of SampEn implies that the signal is very much unpredictable and a low SampEn value implies the signal is redictable. SampEn is computed as follows

$$sampen = \log(\frac{P}{Q}) \qquad (2.3)$$

Where P contains the total number of vector pairs of length *1 + m* and Q contains a total number of vector pairs of length *m* that are matching pointwise within the tolerance or similarity. The value of *m* is taken as 2 in this work and *r* is taken as 0.2 times the standard deviation of the signal.

Largest Lyapunov Exponent

Chaos has always been an interesting fact to find out for decades. Chas arises from the characteristic of a system called Sensitive Dependence on Initial Conditions (SDIC). When an infinitesimally small perturbation is given to the initial state of the system, the way which the new and old states travel in the state space or phase space in the due course of time is the key to observing the chaotic behaviour of the system. If the two trajectories starting with initial conditions separated by infinitesimally small perturbation are evolving with time as exponentially diverging trajectories then it is an indication of chaos. The mean rate of divergence is called Lyapunov Exponent (λ). If the trajectories converge as course of time then we say that chaotic nature is absent. The philosophy is that we assume our EEG time series as the state vector of a system like a brain and using this we estimate the state of the brain to be chaotic or not. For diverging trajectories, Lyapunov exponent is positive and converging trajectories it is negative. The more positive the Lyapunov Exponent be the more chaotic behaviour. For different perturbations of initial conditions we have different Lyapunov exponents often called as a Lyapunov spectrum. The largest possible value of exponent among the spectrum is used as a feature in our work

Let Y_0 and $Y_0+\Delta Y_0$ be the two data points in the phase space. Let us assume that, each of these points will generate an orbit in that space. Let the separation between the two orbits is Δy which is a function of initial condition and time as $\Delta y\ (Y_0,t)$ and will behave unsteadily. Two initially close orbits have the mean exponential rate of divergence as given below

$$\lambda = \lim_{n\to\infty} \frac{1}{t}\, \frac{\ln|\Delta y(y_0,t)|}{\Delta y_0} \qquad (2.4)$$

Box-Cox Transformation

Box-Cox transformation is quite popular time series analysis method in financial analysis and macroeconomic analysis. It is a transformation of the sampled time series into a new time series and the transformation is as follows

$$x_t(p) = \begin{cases} \frac{x_t^p - 1}{p} \; for\ p \neq 0 \\ \ln x_t \;\; for\ p = 0 \end{cases} \qquad (2.5)$$

x_t is the EEG time series and p is the transforming parameter. When p is equal to one it means the transformed time series is on its original scale. When p is equal to zero it is nothing but a logarithmic transformation. In our work, we have used p=0.4 as the transformation parameter. After obtaining the transformed series we extract the Mean Absolute Deviation (MAD) of that series.

3. CLASSIFIERS

After the features are extracted they are given as input to the classifier. Here in our case, we give input feature vectors of all the four features used instead of giving a single feature vector. In another sense, our input is a feature matrix. Three classifiers are used namely Artificial Neural Network (ANN), Support Vector Machine (SVM), Probabilistic neural network (PNN)

Support Vector Machine Classifier

Support vector machine (SVM) is one of the popular machine learning tools. It is mainly used to classify the data by separating them by nonlinear or linear boundaries. The in lying concept involved here is classifying the given input data into pre-specified classes as defined by us. For this, the data is transferred into a higher dimensional space and the data is marked as points in the space. Now the aim of this classifier will be to construct a surface called hyperplane which clearly separates the data points into different sections or classes. The data points which are nearer to the hyperplane will only have an influential part in deciding the hyperplane and these points are called as Support vectors. The points which are far away deep rooted are of least priority. The best choice of hyperplane will be the surface that possesses maximum possible margin for both the classes. In our case, we assign class label 1 to feature vector of normal EEG and label 2 to epileptic EEG. The classifier is trained with the input data using SVM classifier commands in MATLAB. After the training is done we test the data with some test EEG and we see whether it is being labeled appropriately.

ANN Classifier

The ANN classifier uses regression analysis to classify the data. Unlike the other two classifiers, we will not have any class labels here but we define a target vector which is nothing but the desired output of the network. The model of the classifier is the Multi-Layer Perceptron Neural Network (MLPNN) model. This follows supervised learning mechanisms for classification. This a part of the category of feed forward back propagation network. This classifier uses tan-sigmoid activation function in hidden layers while the output layer is linear activation function. The training algorithm used here is Levenberg - Marquadrt Algorithm (LMA). The target element is defined as 0 corresponding to normal EEG signal and 1 corresponding to epileptic EEG signal. After the classifier is trained it is tested with test EEG data and the performance of this classifier is observed.

PNN Classifier

A probabilistic neural network (PNN) has 3 layers of nodes. The input layer (on the left) contains N nodes: one for each of the N input features of a feature vector. These are fan-out nodes that branch at each feature input node to all nodes in the hidden (or middle) layer so that each hidden node receives the complete input feature vector *x*. The hidden nodes are collected into groups: one group for each of the K classes

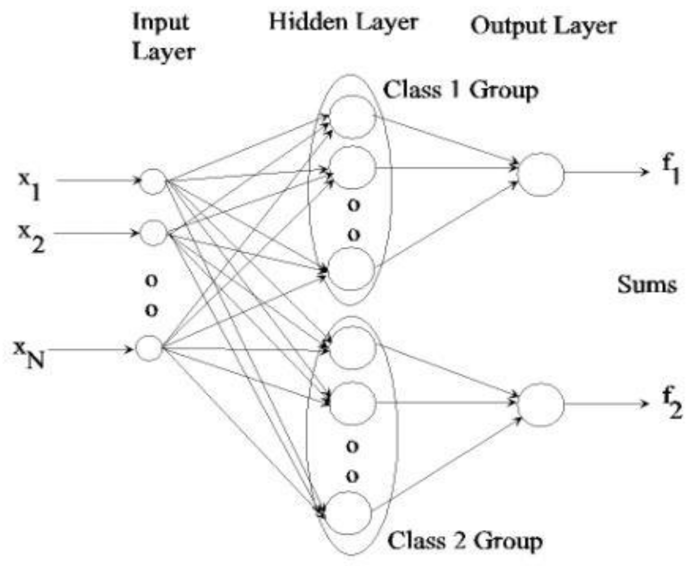

Fig 3.1 Architecture of Probabilistic neural network

The hidden layer consists of the Gaussian functions formed using the given set of data points as centers. The output layer performs an average operation of the outputs from the second layer for each class. There is one more layer which is the fourth layer that performs a vote, selecting the largest value. The associated class label is then determined accordingly.

4. RESULTS

4.1 Feature values

The extracted feature values range in the form of (mean± standard deviation) are tabulated as below

S.No	**Feature**	**Normal Mean ±stdev**	**Epileptic Mean ±stdev**
1	Hurst Exponent	0.685±0.045	0.452±0.097
2	Katz Fractal Dimension	1.426±0.050	2.107±0.338
3	Sample entropy	1.972±0.125	1.047±0.305
4	Largest Lyapunov Exponent	0.209±0.035	0.122±0.213
5	Box Cox Transformation with MAD	3.844±0.168	7.307±0.987

4.2 Classifier performance for noise-free data

As said earlier the classifier receives the five feature vectors fed simultaneously in the form of a matrix as input. This input data is used for training the classifier so that it can clearly differentiate between normal epileptic EEG signals. The performance of the classifier can only be evaluated once it is tested. There are certain parameters which are used to measure the performance of the classifier, they are Sensitivity (true positive ratio), Specificity (true negative ratio), and Accuracy.

$$Sensitivity = \frac{no.of\ true\ positives}{total\ no.of\ positives} * 100 \quad (4.1)$$

$$Specificity = \frac{no.of\ true\ negatives}{total\ no.of\ negatives} * 100 \quad (4.2)$$

True positive is correctly identified and true negative is correctly rejected.
The performance of the three classifiers are compared as shown below

Classifier	*Sensitivity*	*Specificity*	*Accuracy*
SVM Classifier	100%	100%	100%
ANN Classifier	99%	99%	99%
PNN Classifier	100%	100%	100%

4.3 Classifier performance for noisy data

The EEG data is now added with a random signal which makes the EEG data now to be noisy. The amplitude order of random signal is taken in the around 10 and later increased to the order of 100. The classifier performance was compared with the noisy data and is as follows

	Classification Efficiency or Accuracy		
Amplitude of the random signal(noise)	*ANN*	*SVM*	*PNN*
10	100%	100%	100%
25	50%	94%	100%
100	23%	33.33%	100%

In this way, we observe the overall performance of classifiers.

CONCLUSIONS

An automatic diagnosis system for detection of the diseases like Epilepsy can be a very useful assistive device for physicians. Also, it can be used as a primary stage of diagnosing or alarming patients in case of remote location primary health care centers. The work can also be further extended to various types of brain disorders like Alzheimer’s, Parkinson's disease, Amnesia etc.

REFERENCES

1. J. Gotman, Automatic recognition of epileptic seizures in the EEG, electroencephalography Clin. Neurophysiol. 54, 530, 1982.
2. Haselsteiner, E., and Pfurtscheller, G.," Using time-dependent neural networks for EEG classification." IEEE Trans. Rehabil. Eng. 8:457–463, 2000 doi:10.1109/86.895948.
3. Y. U. Khan and J. Gotman," Wavelet-based automatic seizure detection in the intracerebral electroencephalogram." Clin. Neurophysiol. 114, 898 (2003).
4. Thasneem Fathima, M. Bedeeuzzaman, and Paul K. Joseph, "Wavelet-Based Features for Classification of Normal, Ictal and Interictal EEG Signals", Journal of Medical Imaging and Health Informatics Vol. 3, 301–305, 2013.

5. Swiderski, B., Osowski, S., and Rysz, A., Lyapunov Exponent of EEG Signal for Epileptic Seizure Characterization. Proceedings of the 2005 European Conference on Circuit Theory and Design. 2 (28):153–156, 2005.
6.B. S. Raghavendra, and D. Narayana Dutt, " Computing Fractal Dimension of Signals using Multiresolution Box-counting Method ", World Academy of Science, Engineering and Technology International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering Vol:4, No:1, 2010.
7. Ashwani Kumar Tiwari, Ram Bilas Pachori, Vivek Kanhangad, and B. K. Panigrahi, " Automated Diagnosis of Epilepsy using Key point Based Local Binary Pattern of EEG Signals ", IEEE Journal of Biomedical and Health Informatics, 2168-2194 (c) 2016.
8. U Rajendra Acharya, H. Fujita, Vidya K Sudarshan, Shreya Bhat, Joel E.W.Koh " Application of entropies for automated diagnosis of epilepsy using EEG signals: A review", Knowledge-Based Systems 88 · August 2015 DOI: 10.1016/j.knosys.2015.08.004
9. U. Rajendra Acharya, K. Paul Joseph, " Heart rate variability: a review", Med Bio Eng Comput. 44:1031–1051, DOI 10.1007/s11517-006-0119-0, (2006).
10. http://epileptologie-bonn.de/
11. https://www.physionet.org
12. http://hypertextbook.com/chaos/

