Journal of Theoretical and Applied Information Technology
15 August 2012. Vol. 42 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

QUALITATIVE DIAGNOSTIC CRITERIA INTO OBJECTIVE QUANTITATIVE SIGNAL FEATURE CLASSIFICATION

[1]B.SUGUNA NANTHINI, [2]B.SANTHI
[1]Research Scholar, Sastra University,Thanjavur,Tamilnadu,India-613402
[2]Prof, School of computing, Sastra University, Thanjavur, Tamilnadu, India-613402
E-mail: bs.nanthini@gmail.com, shanthi@cse.sastra.edu

ABSTRACT

Predicting the epileptic seizure is challenging biomedical problem. EEG signal includes enormous information. Few relevant parameters are expected in the field of recognition and diagnostic purposes. Seizure detection and classification system has been designed and developed. The system uses computer based procedures to detect seizure and classified normal and abnormal subjects. Intelligent compact support property of GLCM is used for extracting essential features from the EEG signal. Selected features are classified using neural network model. The 70 samples would be divided into 50 training samples and 20 testing samples. The back propagation algorithm tested on these samples showed expected classification. The main objective of this study is to predict the epileptic seizure using GLCM feature extraction method and neural network model.

Keywords: *Seizure, EEG Signal, GLCM, Neural Network, Accuracy*

1. INTRODUCTION

Human cerebral system which consists of brain has an excellent and rich spatiotemporal dynamics which is especially unique to human. EEG provides us a record of the electrical action potentials produced by cerebral cortex neurons. Epileptic seizures are existence of epilepsy [1]. Analyses of EEG records can afford valuable insight and enhanced understanding of epileptic disorders. Highly developed techniques for the analysis of EEG signals are vital in the area of biomedical research. There is demand for the development of automated devices, due to the increased use of EEG recordings. EEG helps in the evaluation and treatment of neurological diseases. The conventional method of signal analysis is not successfully recognized in diagnostic classification. As EEG signals are non stationary, there are many limitations [2]. The function of the brain is recorded by EEG, but classification and evaluation of these signals are limited. According to the experts in this field, visual analysis of EEG signals in time may be insufficient. Routine clinical diagnoses are needed for analysis of EEG signals. Recurring seizure are characterized epilepsy. EEG measures the abnormal electrical activity in the brain which causes altered perception and behaviour. Various pattern recognition methods for automated diagnosis have been adopted. The entire process can be subdivided into number of processing modules: segment detection, feature extraction/selection, and classification (Figure 1). Quantitative signal features can be detected by automated EEG event detection technique from the qualitative diagnostic criteria. EEGs are important measurements of brain activity and they have great potential for the diagnosis and treatment of mental and brain diseases and abnormalities. The information within EEG Signal Processing has the potential to enhance the clinically-related information within EEG signals, thereby aiding physicians and ultimately providing more cost effective, efficient diagnostic tools. It will be beneficial to psychiatrists, neurophysiologists, engineers, and students or researchers in neurosciences [4].

The paper is organised as follows. In Section 2 research issues of EEG classification are discussed. Section 3 deals with material and methods. Section 4 gives evaluation of performance, followed by conclusion at section 5.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

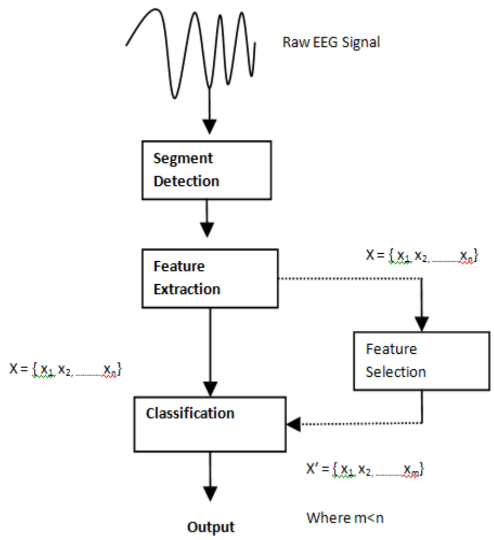

Figure 1. Functional modules in a typical computerized EEG system

2. RESEARCH ISSUES OF EEG CLASSIFICATION

In this part, researchers' work on epileptic EEGs classification is briefly reviewed. Abdulhamit Subasi and Ergun Ercelebi, [1] extracted features of EEG signals using wavelet transform and classification using artificial neural network (ANN) and Logistic regression (LR). Delta, theta, alpha and beta sub frequencies of EEG signals were extracted by using Lifting-Based Discrete Wavelet Transform (LBDWT). LBDWT Co-efficient of EEG was used as an input to logistic regression and multilayer perceptron neural network (MLPNN) used to detect epileptic seizure. Classifiers have been developed and trained depending on these sub frequencies. In this paper, two approaches to develop classifiers for identifying epileptic seizures were discussed. One approach is based on the traditional method of statistical logistic regression analysis where logistic regression equations were developed. The other approach is based on the neural network technology, mainly using MLPNN trained by the back propagation and L-M algorithm. Subasi,[14] [15] [16] moulded the EEG signals into time-frequency representations using discrete wavelet transform. Some features based on DWT were obtained and applied for different classifiers for epileptic EEG classification, such as feed-forward error back-propagation artificial neural network(FEBANN), dynamic wavelet network (DWN), dynamic fuzzy neural network (DFNN) and mixture of expert system (ME).

Elif Derya Ubeyli,[6] in her study, the EEG signals classified using the combined neural network for classification. In the development of combined neural network for classification of the EEG signals, for the first level models three sets of neural networks were used since there were three diagnostic classes. Networks in each set were trained by Levenberg-Marquardt algorithm so that they are likely to be more accurate for one type of EEG signal than the other EEG signals. Thus combined neural network used for classification of the EEG signals was trained, cross validated and tested with the extracted features using discrete wavelet transform of the EEG signals. The accuracy rates achieved by the combined neural network model presented for classification of the EEG signals were found to be higher than that of the stand-alone MLPNN trained with the back propagation algorithm.Umut Orhan,et al., [19] used a MLPNN-based classification model to classifiy EEG signals. EEG signals were decomposed into sub-bands through the DWT. Instead of using basic statistics over the wavelet coefficients, this study used the clustering approach for the wavelet coefficients in each sub-band by using K-means algorithm and performed five different experiments to obtain the performance of the model.Deng Wang, et al., [4] implemented the best basis-based wavelet packet entropy feature extraction method in the training stage to acquire fewer feature spaces of EEG signals, and in combination with the cross-validation, a hierarchical Knowledge base (HKB) was constructed. In testing stage, the discriminative rules from HKB were chose for final classification according to minimal conference level (MCL). This method was successfully applied to EEG signals for the epileptic detection.In the study presented by Ubeyli and Guler, [18] decision making was carried out in two stages: feature extraction by eigen-vector methods and classification using the specified classifiers which was trained on the extracted features. The inputs of these expert systems composed of diverse or composite features were chosen according to the network structures. The five-class classification accuracies of expert system with diverse features (MME) and with composite feature (ME) were 95.53% and 98.6%, respectively.Ling Guo, et al., [10] used Genetic programming (GP) to create new features from original feature database to improve the KNN classifier performance and simultaneously decrease the input feature dimension for the classifier. The input feature was automatically determined during

Journal of Theoretical and Applied Information Technology
15 August 2012. Vol. 42 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

GP evolution, not fixed beforehand or decided by humans.

3. MATERIALS AND METHODS

3.1. EEG data description

In this study, a publicly available EEG database (EEG time series) was experimented. This session will give a short description and refer to Andrzejak et al, [3] for further details. The five data sets (A-E) each contain 100 single channel EEG segments of 23.6s duration. These segments were selected under visual inspection and slice out from continuous EEG recordings for artifacts (muscle activity or eye movements). Using the standardized electrode placement scheme where five healthy volunteers were selected and EEG recording were carried out using sets A and B which consists of segments taken from those surface EEG recordings. (Figure. 2). Volunteers were divided into A and B, and A comprises those relaxed in an awaken state with eyes open and set B relaxed in an awaken state with eyes closed. Using EEG archive of presurgical diagnosis sets C, D and E were selected.

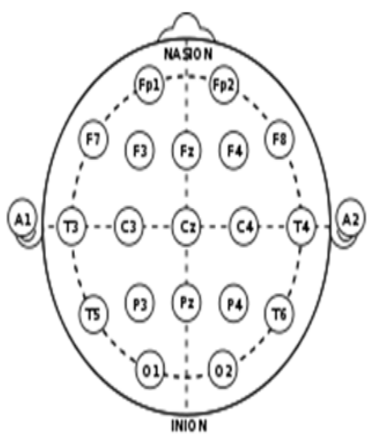

Figure 2: Diagram showing 10-20 system of electrode placement

The results were recorded as follows: The segments in set D showed the recordings from within the epileptogenic zone. Set C and D showed activity measured during seizure free intervals. Set E showed only seizure activity. Using an average common reference with 128-channel amplifier most of the EEG signals were measured. By 12 bit resolution, the data measurements were digitized at 173.61 samples per second. With 0.53-40Hz (12db/oct) the band-pass filter settings were set (Andrzejak et al., [3]). Dataset (A and E) were used in this study. Characteristic EEGs from Set A and E are depicted in Figure 3.

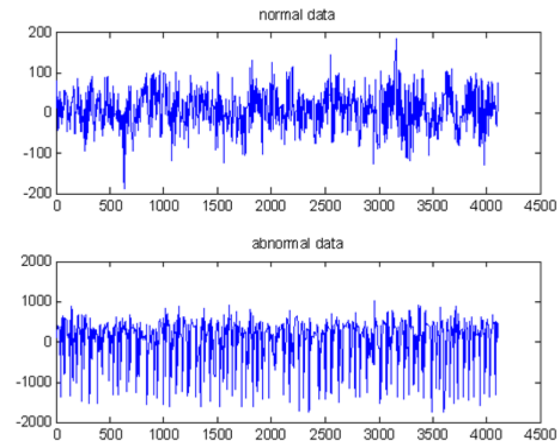

Figure3. Plot of Normal and Abnormal Signal

3.2 EEG Feature Extraction

The EEG signal features are extracted using GLCM (Gray level Cooccurrence matrix).A cooccurrence matrix C is defined over n*m and image I parameterized by an offset ($\Delta x\ \ \Delta y$) as

$$C_{\Delta x\,\Delta y}\,(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, if\ I(p,q)=i\ and\ I(p+\Delta x,q+\Delta y)=j\\ 0\ otherwise\end{cases}$$

Here In this study, each signal waves are considered as an image. The grayscale value of the specified pixels are identified by the value of the image. Any matrix or pair of matrices can be used to generate a cooccurrence matrix which measures the texture in image.The sample GLCM features for normal and abnormal subjects are shown in Table 1 and Table 2.

Table 1: GLCM features for 5 Normal Subjects

Features	Contrast	Correlation	Energy	Homogeneity
Subject 1	24.2813	-0.0080	0.2584	0.5664
Subject 2	10.6823	0.0042	0.6106	0.8092
Subject 3	23.6493	-0.0117	0.2733	0.5777
Subject 4	23.9045	0.0162	0.2543	0.5731
Subject 5	21.8385	-0.0190	0.3156	0.6100

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: GLCM features for 5 Abnormal Subjects

Features	Contrast	Correlation	Energy	Homogeneity
Subject 1	22.3125	-0.0477	0.3174	0.6016
Subject 2	24.6094	-0.0317	0.2632	0.5605
Subject 3	23.0052	0.0067	0.2783	0.5892
Subject 4	24.7309	-0.0109	0.2507	0.5584
Subject 5	22.6042	0.0593	0.2612	0.5964

3.3 Back-propagation Neural Network

Feed forward back-propagation network is used to classify the EEG signals. Selected features from the EEG are used to train and test the network for classifications of normal and abnormal patterns. A Multi layer perceptron (MLP) is used for solving pattern classification problems where supervised learning is implemented using back propagation algorithm (Figure 4).The strength of using this type of ANN is fast execution of trained network which is advantageous in signal processing application. The back-propagation algorithm is as follows:

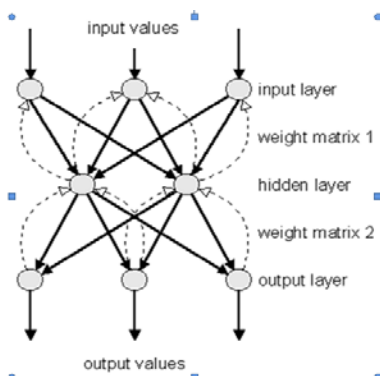

Figure 4: Back-propagation Neural Network

The activation function of the artificial neuron:

$$A_j(\bar{x},\overline{w}) = \sum_{i=0}^{n} x_i\, w_{ji} \quad (1)$$

The output function is the signoidal function:

$$O_j(\bar{x},\overline{w}) = \frac{1}{1+e^{A(\bar{x},\overline{w})}} \quad (2)$$

The error function for the output neuron:

$$E_j(\bar{x},\overline{w},d) = (O_j(\bar{x},\overline{w}) - d_j)^2 \quad (3)$$

Sum of the errors of all the neurons in the output layer:

$$E_j(\bar{x},\overline{w},d) = \sum_j (O_j(\bar{x},\overline{w}) - d_j)^2 \quad (4)$$

Weight adjustment using the method of gradient descendent:

$$\Delta w_{ji} = -\frac{\partial E}{\partial w_{ji}} \quad (5)$$

Error dependency calculation on the output (from (3)) and output dependency on the activation, which depends on the weights (from (1) and (2)):

$$\frac{\partial E}{\partial O_j} = 2(O_j - d_j) \quad (6)$$

$$\frac{\partial O_j}{\partial w_{ji}} = \frac{\partial O_j}{\partial A_j}\frac{\partial A_j}{\partial w_{ji}} = O_j(1-O_j)x_i \quad (7)$$

From (6) and (7)

$$\frac{\partial E_j}{\partial w_{ji}} = \frac{\partial E_j}{\partial O_j}\frac{\partial O_j}{\partial w_{ji}} = 2(O_j - d_j)O_j(1-O_j)x_i \quad (8)$$

The adjustment to each weight will be (from (5) and (8)):

$$\Delta w_{ji} = 2(O_j - d_j)O_j(1-O_j)x_i$$

The forward and backward sweeps continue until ANN solution agrees with the desired value within a pre-specified tolerance. The non linear behaviour of the back-propagation network allows the perceptron to generate complex decision regions, which is a desirable property in pattern classification.

3.4 Methodology and Result

Table 3: Training and Testing Patterns

No. of training samples	50
No. of Epileptic Training samples	25
No. of Normal training samples	25
No. of testing patterns	20

The neural network was trained using 50 datasets and tested using a new set 20 epileptic and non epileptic data. The multilayer network was used with neurons or processing elements having a sigmoid transfer function. Input and target vectors were train the network until the network classified the input vectors correctly. Best validation performance show in Figure 5.

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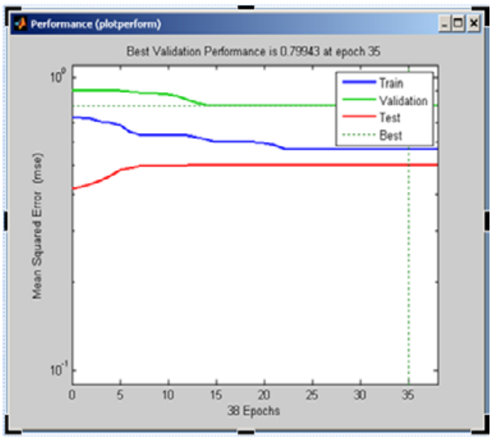

Figure 5: Training of designed Back-propagation Network

4. EVALUATION OF PERFORMANCE

A value of "0" was used when the experimental investigation indicated a normal EEG pattern and "1" for epileptic seizure. Prediction success of the classifier may be evaluated by examining the confusion matrix. In order to analyse the output data obtained from the application, TPR (true positive ratio) and TNR (true negative ratio) are calculated by using confusion matrix. Sensitivity, specificity and total classification accuracy are calculated by the following formula.

$$\text{Sensitivity} = \text{TPR} = \frac{TP}{TP+FN} * 100\%$$

$$\text{Specificity} = \text{TNR} = \frac{TN}{TN+FP} * 100\%$$

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)} * 100\%$$

Table 4: Performance measures

Actual	Predicted	
	Normal (Positive)	Abnormal (Negative)
Normal (Positive)	10 (TP)	0 (FP)
Abnormal (Negative)	3 (FN)	7 (TN)

Table 5: Values of performance measures

Measures	Values (%)
Sensitivity	76
Specificity	100
Total Classification Accuracy	85

The neural network model classified the normal and abnormal subjects with the accuracy of 85%. Table 4 shows the confusion matrix of the classification. The performance measures are calculated for three independent features are shown in figure 6.

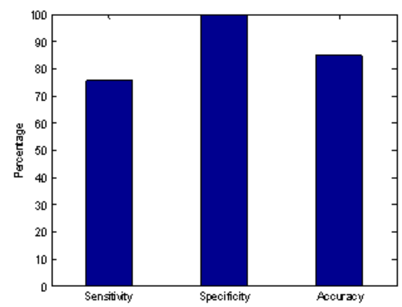

Figure 6: Performance Analysis

5. CONCLUSION

Epilepsy is the most common serious neurological disorders characterized by unprovoked seizures. Diagnosing epilepsy is a difficult task requiring observation of the patient, an EEG and gathering of additional clinical information. Hence automated detection is a foremost tool in epilepsy diagnosis. Neural Network that is used in this study has 20 hidden nodes, 0.05 learning rate, and 0.9 momentum rate. This study is based on small data set. In future this limitation may be overcome by collecting more number of records. This may improve the decision rate. There are many EEG feature extraction method are available. Comparison between the different methods of feature extraction and classifiers are lacking in this study. Feature Extraction using GLCM has shown good result in this study and neural network has classified epilepsy for the given set of data with excellent performance. In near future, other feature extraction method (wavelet transform) can be applied to this data sets and other classifiers (SVM) can be used for automated epilepsy diagnosis.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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