World Applied Sciences Journal 29 (Data Mining and Soft Computing Techniques): 65-69, 2014
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2014.29.dmsct.12

EEG Signal Analysis for Epileptic Seizure Detection Using Soft Computing Techniques

B. Suguna Nanthini and B. Santhi

School of Computing,
Sastra University, Thanjavur, Tamilnadu, India-613402

Abstract: Seizure activity takes place due to an irregular excessive electrical action in the human brain. The electrical activity in the form of brain waves (signals) can measured by using the device called Electroencephalogram (EEG). In this paper, we have reviewed our work so far made regarding EEG signals. Comparative between Artificial Neural Network (ANN) and Support Vector Machine (SVM) this review has shown that SVM is the successful classifier to classify the normal and abnormal EEG signals. Moreover, this paper emphasizes the application of wavelet decomposition and feature extraction for EEG signal analysis. The main objective of this study is to analyze EEG signal for epileptic seizure detection.

Key words: EEG · Seizure · GLCM · Shannon · Wavelet transform · SVM · ANN · Accuracy

INTRODUCTION

The Human cerebral system consists of the brain has an excellent spatiotemporal dynamics which are unique to human. EEG provides the electrical action potentials produced by cerebral cortex neurons [1]. The EEG detecting machine is a video recording device and linked through wires to electrodes connected at specific points on the head of the patient [2]. A Seizure is a paroxysmal event due to irregular excessive hypersynchronous neuronal discharge [3]. Epilepsy is also known as the seizure disorder because the irregular action of the nervous system which is causing periodic loss of consciousness or convulsions. Special sensors (electrodes) are attached to the scalp to diagnose epilepsy and record what types of seizures are occurring [4]. The types of EEG waves are identified as Delta Below 3.5Hz range from 0.1 to 3.5 Hz; Theta ranges from 4 to 7.5 Hz; Alpha ranges from 8 to13Hz; Beta ranges from 14 to 40 Hz; and Gamma ranges above 40 Hz [5, 6]. The scalp EEG is the generally accepted test for the clinical diagnosis of epilepsy [7, 8]. EEG is a multidimensional, non-stationary, time-domain biological signals [9]. The general process of seizure detection includes feature extraction, feature selection and classification of normal and abnormal of EEG signals (Figure 1).

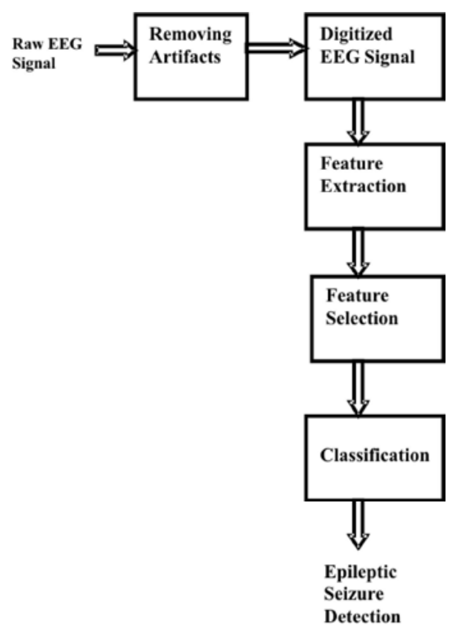

Fig. 1: General Process of Seizure Detection

Quantitative signal features can be detected by automated EEG event detection technique from the qualitative diagnostic criteria [1]. In this review paper we have analyzed four different studies what we have made so far. Study one detected the epileptic seizure by

Corresponding Author: B. Suguna Nanthini, Research Scholar, School of Computing, Sastra University, Thanjavur, Tamilnadu, India-613402.

extracting Gray level Cooccurrence matrix (GLCM) features (Contrast, Correlation, Energy, Homogeneity) and classified the EEG signals using Artificial Neural Network (ANN) model.

As it was done in the study one [1], GLCM is used for extracting essential features from the EEG signal in the study two [4] and compared the performance of the classifier Support Vector Machine (SVM) method for seizure detection. Study one and two analyzed the seizure detection results without using wavelet decomposition. Study three overcomes this limitation by the uses of discrete wavelet transform. The brain wave EEG signals were decomposed by using db1, db2 (Daubechies wavelet) and Haar wavelet. GLCM, statistical features (Mean, Median, Mode, Standard Deviation, Skewness and Kurtosis) and hybrid (combining GLCM and Statistical) features were extracted from the decomposed EEG signal. The main principle of this study three is to observe the performance of classifiers regarding SVM and ANN using wavelet coefficients for seizure detection. Mostly GLCM features are used for texture analysis in Image processing. It is innovative that we have used GLCM features for EEG signal processing. Though GLCM features yield good results for seizure detection, we tried the EEG analysis using Shannon Entropy for decomposed EEG signals in study four for better classification accuracy. The values obtained from the Shannon entropy are applied as an input to the SVM classifier. This paper is arranged as follows. In Section 2 Data sets used for EEG analysis are discussed. Section 3 describes the importance of Wavelet decomposition. Section 4 deals Results of EEG Signal Analysis, followed by a Conclusion at section 5.

Data Sets for EEG Analysis: The online available EEG database was experimented in all the analyses done in the four papers. The following few words give short description about data set and for more details refer [10]. In the five data sets A to E, each contains details of 100 subjects (100 single channel EEG segments) with the duration of 23.6s. From continuous EEG recordings these segments were selected for removing artifacts such as muscle activity or eye movements. Using the 10-20 standardized electrode placement scheme, data set A relates those who relaxed in an awaken state with eyes open and set B relates with eyes closed. Data set C and D measured during seizure free intervals. Set E showed only seizure activity. With 128-channel amplifier, by 12 bit resolution, the data measurements were digitized at 173.61

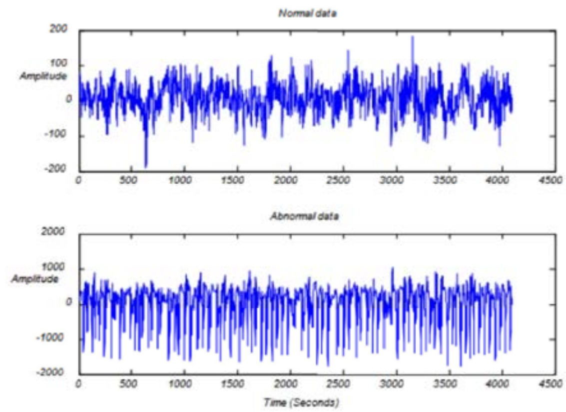

Fig. 2: Plot of Normal and Abnormal EEG Signal

samples per second. With 0.53-60Hz (12db/oct) the band-pass filter settings were set [10]. Dataset (A and E) was used in all the four studies. Figure 2 shows the EEG signal characteristics of normal subject from a data set A and abnormal subject from data set E.

Wavelet Decomposition: Study one and two analyzed the EEG signal without wavelet decomposition. Since wavelet is the powerful tool to analyze the components of non-stationary EEG signals, to emphasize the importance of wavelet, study three and four analyzed EEG signal by using wavelet decomposition. In study three, using discrete wavelet transform the EEG signal both normal and abnormal were decomposed at level 3 by db1, db2 and haar wavelet associates. This study three concluded that db2 and SVM were the best combination for EEG analysis. For better approximation, in study four we had decomposed the EEG signal at level 4 by using db2. As our dataset is in the order of 0-60Hz raw EEG, the sub bands D1, D2, D3, D4 and A4 were decomposed to the frequency of 30-60Hz, 15-30Hz, 8-15Hz, 4-8Hz and 0-4Hz respectively. The Shannon Entropy was determined for each sub bands as well as for the raw EEG signal. Then the values from each sub bands and raw EEG acted as an input to the SVM classifier for seizure detection.

Results of EEG Analysis: Using GLCM features of normal and abnormal subjects study one and two were analyzed the performance of the classifiers for 70 samples which would be divided into 50 training samples and 20 testing samples. Table 1 shows the sample GLCM features for normal and abnormal subjects obtained from study one.

Table 1: GLCM features for normal and abnormal subjects obtained from study one

Features	Subjects	Contrast	Correlation	Energy	Homogeneity
Normal	S1	22.0816	0.0165	0.2944	0.6057
	S2	24.1962	-0.0977	0.3002	0.5679
	S3	25.8003	-0.0813	0.2637	0.5393
Abnormal	S1	19.7969	0.1338	0.2928	0.6465
	S2	24.7066	-0.0113	0.2514	0.5588
	S3	24.1233	-0.0151	0.2651	0.5692

Table 2: Statistical features for approximation signal by using db2 at level 3 from study three

Features	Subjects	mean	Std Deviation	median	mode	skewness	kurtosis
Normal	NS1	19.6184	99.7745	20.8597	-43.4871	-0.2345	3.5839
	NS2	-148.4786	107.3429	-145.6640	-253.1442	-0.2205	3.5141
	NS3	36.2699	110.1132	36.7696	83.4386	0.0737	3.2320
Abnormal	AS1	0.1352	1.0270	0.3702	1.0437	-0.0008	0.00031
	AS2	0.1070	1.0708	0.1743	0.3338	-0.0003	0.0028
	AS3	0.0905	0.6954	0.1761	-0.0665	-0.0002	0.0030

Table 3: Comparison of Classification results by using db2 wavelet from study three

	Wavelet Co-efficient	Extracted Features	Neural Network Sensitivity %	Neural Network Specificity %	Neural Network Accuracy %	SVM Sensitivity %	SVM Specificity %	SVM Accuracy %
db2	cA3	GLCM	71.4	61.5	65	72.7	77.7	75
		Statistical	100	100	100	100	100	100
		GLCM and Statistical	100	100	100	100	100	100
	cD3	GLCM	90	90	90	100	90.9	95
		Statistical	100	90.9	95	100	100	100
		GLCM and Statistical	100	100	100	100	90.9	95
	cD2	GLCM	88.8	81.8	85	90	90	90
		Statistical	62.5	100	70	90.9	100	95
		GLCM and Statistical	90.9	100	95	90.9	100	95
	cD1	GLCM	87.5	75	80	88.8	81.8	85
		Statistical	90.9	100	95	90.9	100	95
		GLCM and Statistical	75	87.5	80	90.9	100	95

From study two, Figure 3 shows the classification of subjects using SVM. SVM recognized by hyperplane that separates normal and abnormal subjects with minimum misclassification.

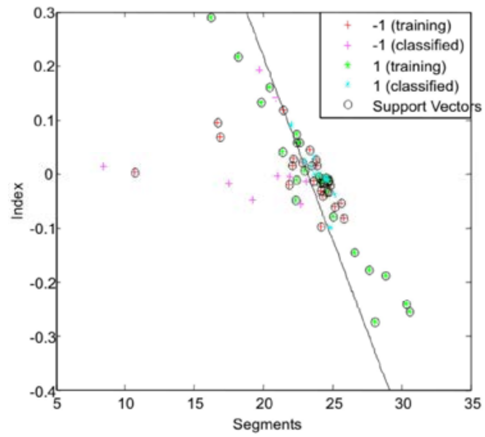

Fig. 3: SVM 2D plot using GLCM features

For the same set of samples, in study three the EEG signals were decomposed by db1, db2 (Daubechies wavelet) and Haar wavelet. GLCM, Statistical features and Hybrid features were extracted from the decomposed EEG signal. The sample statistical features for approximation signal by using db2 at level are shown in Table 2.

Table 3 shows the comparison of classification results by using db2 wavelet from study three. The SVM classified the normal and abnormal subjects with the accuracy of 75% compared to an ANN accuracy of 65% with GLCM features by using db2 wavelet at approximation coefficient (cA3).Regarding statistical features and hybrid features both ANN and SVM achieved 100% accuracy. So performances of these classifiers in approximation coefficient are efficient. Similarly we analyzed the classification results for detail coefficients also. By overall comparison with db1 and haar wavelet coefficient values this study three concluded that SVM classifies by using db2 with hybrid features are the best outcomes for EEG signal classification.

A systematic analysis of EEG for seizure detection using wavelet based features had presented in study three. As EEG is a nonstationary signal, the discrete wavelet transform yielded good output and it is proved by study three. After wavelet decomposition at level 3 by using db1, db2 and haar wavelet, six statistical features and GLCM features are well analyzed over the wavelet coefficients at each level. The comparison of the classifier ANN and SVM is also well analyzed in study three. Though GLCM features yield good results in first three analyses for the small set of data samples, to get better results Shannon entropy applied to the increased set of data samples in study four. Shannon Entropy was measured for decomposed signals and applied as the

Table 4: Shannon Entropy for decomposed EEG signals by using db2 at level 4 from study four

Features	Subjects	Raw	A4shn	D4shn	D3shn	D2shn	D1shn
	NS1	-0.1271	-0.0466	-0.0650	-0.0771	-0.0163	-0.0017
Normal	NS2	-0.1947	-0.0849	-0.1017	-0.0882	-0.0367	-0.0034
1.0e+008	NS3	-0.1073	-0.0308	-0.0763	-0.0826	-0.0197	-0.0026
	AS1	-0.9663	-0.0543	-0.1077	-0.0478	-0.0065	-0.0005
Abnormal	AS2	-0.6021	-0.0962	-0.1692	-0.1835	-0.0473	-0.0047
1.0e+010	AS3	-0.1794	-0.0690	-0.0650	-0.0275	-0.0041	-0.0004

Table 5: Performance classification measures from all the studies

Performance Measures	Study one (ANN with GLCM features)	Study two (SVM with GLCM features)	Study three (ANN with hybrid features)	Study three (SVM with hybrid features)	Study four (SVM with Shannon Entropy)
Sensitivity	100	90	91.4	95.5	90.9
Specificity	76	90	96.8	97.7	100
Accuracy	85	90	93.8	96	95

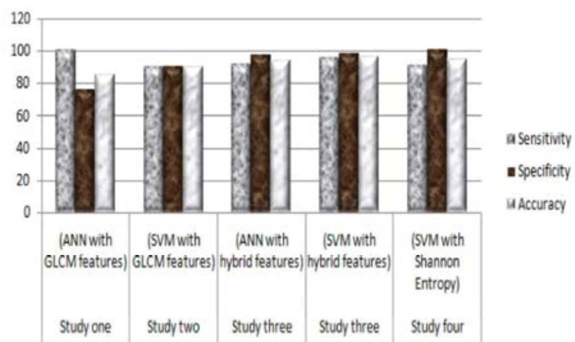

Fig. 4: Performance measures of the classifiers ANN and SVM

input to the SVM classifier for seizure detection. Table 4 shows sample values of Shannon Entropy for the decomposed EEG signal.

Table 5 shows the performance classification measures of all the four studies. Study three measured the average value of all the sub bands. We have focused on hybrid (GLCM and Statistical) features because it yields good output by the classifiers. The SVM classified the normal and abnormal subjects with the accuracy 96% using hybrid features during study three.

Performance measures of the classifiers are estimated for three independent features such as sensitivity, specificity and accuracy are shown visually in the Figure 4.

CONCLUSION

In this paperwork, we have analyzed four different studies which we have done in our previous papers regarding EEG signals with various features and classifiers. From table 5, comparing the performance of ANN and SVM, this paper concludes that SVM is the successful classifier to classify the normal and abnormal subjects. Moreover this review of four different analyses ascertains the importance of wavelet decomposition at level 4 to get brain wave delta (0-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (30-60Hz). So far in the four different study data set A and E were used for binary classification. To overcome this limitation, in the near future the performance of SVM with other soft computing techniques using different features will be analyzed for multilevel classification.

REFERENCES

1. Suguna Nanthini, B. and B. Santhi, 2012. Qualitative diagnostic criteria into objective quantitative signal feature classification. JATIT, 42: 94-99.
2. Sanei, S. and J.A. Chambers, 2007. EEG signal processing, John Wiley and Sons Ltd.
3. Misra, U.K. and J. Kalita, 2009. Clinical Electroencephalography. Published by Elsevier, a division of Reed Elsevier India Private Limited.
4. Suguna Nanthini, B. and B. Santhi, 2012. Seizure Detection using SVM Classifier on EEG Signal. International Conference on Electrical Sciences (ICES).
5. Ubeyli, E. and I. Guler, 2007. Features extracted by eigenvector methods for detecting variability of EEG signals. Pattern Recognition Letters. 28(5): 592-603.
6. Umut Orhan. Mahmut Hekim. Mahmut Ozer,2011. EEG signals classification using the K-means clustering and a multilayer perceptron neural network model. Expert Systems with Appilications 38: 13475-13481.
7. Subasi, A., 2005. Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients. Expert Systems with Applications, 28(4): 701-711.
8. Subasi, A., 2007. EEG Signal classification using wavelet feature extraction and a mixture of expert model. Expert Systems with Applications, 32: 1084-1093.

9. Kaushik Majumdar 2011. Human scalp EEG processing: Various soft computing approaches. Applied Soft Computing, 11: 4433-4447.

10. Andrzejak, R.G., K. Lehnertz, F. Mormann, C. Rieke, P. David and C.E. Elder, 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. http://epileptologie-bonn. de/cms/ front _ content.php?idcat=193