Analysis on Wavelet Feature and Softmax Discriminant Classifier for the detection of epilepsy

Deepa R¹, Harikumar Rajaguru², Ganesh Babu C³

1. Assistant Professor, Department of EIE, Bannari Amman Institute of Technology, Erode, Tamilnadu, India.
2. Professor, Department of ECE, Bannari Amman Institute of Technology, Erode, Tamilnadu, India.
3. Professor, Department of EIE, Bannari Amman Institute of Technology, Erode, Tamilnadu, India.

*rangarajdeepta@gmail.com, harikumarrajaguru@gmail.com, ganeshbabuc@bitsathy.ac.in

Abstract. The most frequently diagnosed brain disease is epilepsy, which is characterised by the unexpected onset of frequent seizures. The detection of epilepsy in this paper was established by using the wavelet features Haar, dB2, Symlets (Sym8) and dB4, followed by the Softmax Discriminant Classifier, which uses to detect the epilepsy from the EEG signals. The performance of the wavelet features and classifier is evaluated based on the performance index, specificity, sensitivity, precision, time delay and quality values. Among the wavelet features, the Sym8 performs better than the other and processed further using the Softmax Discriminant Classifier, which outperforms the 90.93 percent classification accuracy, with a low time delay of 1.991s, the 72.61 percent output index, the most promising result in this work.

Keywords: EEG Signals, Haar, dB2, Sym8, dB4, Softmax Discriminant Classifier

1. Introduction

The Electroencephalogram (EEG) outlooks a function of the simultaneous neural activity in several portions of the brain. It provides insights into variations in the brain's electrical potential resulting from a series of monitoring electrodes. A widespread range of factors, including biochemical, metabolic, circulatory, hormonal, neuroelectrical and behavioural factors, are said to have affected EEG variations. Throughout the past, the encephalographer was able to qualitatively determine among both usual EEG behaviour and localised or generic disorders reported in significantly longer EEG records by visual observation. Epilepsy is the most pertinent behaviour that can be noticed after the EEG record. Epilepsy is categorised by moreover a portion or more of the central nervous system of uncontrolled repetitive activity or potential discharge. Distinct EEG waveform patterns reflect the various forms of epileptic seizures. Automatic seizure detection algorithms can help doctors easily examine them. Clinical diagnosis of epilepsy needs a thorough history and also a comprehensive history. Neurological assessments to verify the probability of associated causes of biochemical imbalances, along with blood tests and occasionally cerebrospinal fluid tests.

The EEG tends to be an effective therapeutic mechanism for epilepsy diagnosis, examination and treatment [1]. In fact, EEG records the multi-channel signal, as soon as the electrodes are positioned on the scalp. To examine epilepsy, the electroencephalographer inspects the EEG details visually. It is obviously
a difficult task to observe EEG data incessantly for a long time because EEG data recordings usually have an enormous data length. It takes quite a long time to capture EEG signals and can only be interpreted by trained clinicians. This has contributed to the rapid concern in automatically detecting and classifying EEG signals for risk levels of epilepsy. In the biomedical industry, the automated detection of seizures in clinical practices takes an hour and is absolutely necessary.

The paper's organisation describes the materials and methods session, the EEG data collection is defined. The wavelet features are discussed next to the materials and methods. The Softmax Discriminant Classifier in the classifier session is evaluated. The SDC classifier's output is accounted for in the outcome and analysis. Finally, the paper for the future scope is concluded.

2. Materials and Methods

This work uses 20 epileptic patients beneath observation and diagnosis takes place in the Department of Neurology, Sri Ramakrishna Hospital, Coimbatore, India, who have received EEG data[2]. Through 10-20 international electrode placement methods from a clinical EEG monitoring device, a paper record of 16 channel EEG data has been collected. The Investigators selected artefact-free EEG records with distinct characteristics with the aid of a neurologist.

The frequency of the EEG signal utilizes 50 Hz, and every epoch is sampled at 200 Hz. Every sample matches the instantaneous amplitude value of the signal. 400 values in total for an epoch. Every channel has 400 samples of EEG signals per epoch and three epochs of data forms a bin. There are sixteen such bins which are available per patient. The various parameters used to quantify the EEG are evaluated with appropriate programming codes using these amplitude values. These parameters are obtained at discrete time for three distinct continuous epochs to find variants and irregularities in epileptic behaviour. The preparation and testing, utilizes the twenty EEG records. The average length of these EEG records was three seconds and the total length was 120 seconds. This paper proceeds the EEG samples of the 20 patients, and uses the feature extraction techniques followed by SDC and performance measures are analysed are exposed in figure 1.

![Figure 1: Block Diagram of the work](image-url)
3. Feature Extraction uses Wavelet Transforms

Consider the function $y(t)$ with that the wavelet transform is expressed in Eq.1 as

$$w(a,b) = \int_{-\infty}^{\infty} y(t) \psi_{a,b}(t) dt$$  

(1)

Where $\psi^*(t)$ – complex conjugate of the wavelet transform function [3].

The wavelet family is deduced from the mother wavelet $\psi(t)$ with the set of the analysis task is defined in Eq.2 as

$$\psi_{a,n}(t) = \sqrt{a} \psi\left(\frac{t-n}{a}\right)$$  

(2)

Where, $a$ – dilation and $n$ – translation parameter.

By observing the result of the simple Haar threshold, feature extraction process is initialised. The Haar wavelet function is expressed in Eq.3 as

$$\psi(t) = \begin{cases} 
1 ; & 0 \leq t < \frac{1}{2} \\
-1 ; & \frac{1}{2} \leq t < 1 \\
0 ; & \text{otherwise}
\end{cases}$$  

(3)

The signal denoising and/or smoothing, prefers the wavelet thresholding technique.

The Wavelet transform is defined as a mathematical technique in which different versions of a dilated and translated basis function called the mother wavelet used to analyse a specific signal in the time domain[4],[6]. A wavelet feature $\psi(t)$ is a small wave that somehow discriminates between frequencies by being oscillatory. The wavelet includes both the form and the window for study. A building block for functions uses the important characteristics of the wavelet, it has space-frequency localization, supports strong transformation algorithms, and ultimately has the ability to produce lower level coefficients from higher level coefficients together with a symmetric filter[5]. The properties of Haar, dB and Symlet wavelets are described below:

Haar Wavelet: Exactly, it is a discontinuous function and resembles a process function. It represents a wavelet comparable to that of Daubechies dB1. The Haar wavelet is a simplified compression form that includes average and difference terms, stores information coefficients, removes data, and reconfigures the matrix so that it is comparable to the original matrix with the resulting matrix. The only orthogonal and symmetric wavelet that is compactly supported is the Haar wavelet. The compact support of the Haar wavelets allows the Haar decomposition to have a powerful localization of time.

Daubechies: One of the largest stars in the field of wavelet research was created by Ingrid Daubechies, which is effectively supported by orthonormal wavelets, making discrete wavelet analysis possible. The family wavelets of the Daubechies are written as dBN, where the order of the wavelet family is N. These wavelets are compact and orthogonal in nature, which is energy supportive[7],[8].

Symlets: "Symmetrical wavelets" are part of the symlet wavelet family. They are very well designed such that they would have the least symmetry for a given compact support and the maximum number of disappearing moments.

The table 1 describes the EEG signal of epoch 1 of Haar, dB2, sym8 and dB4 wavelet features are taken for all patients, similarly epoch 2 and epoch 3 for all patients are processed.
4. Softmax Discriminant Classifier

SDCs primary purpose is to determine and classify the classification to which a specific test sample belongs. It is truly ready by weighing the distance between the training and the assessment sample of the same class. Suppose the $P = \{ P_1, P_2, \ldots, P_n \} \in \mathbb{R}^{x \times y}$ train set originates from different groups of $i$. $P_n = \{ P_{n1}, P_{n2}, \ldots, P_{nr} \} \in \mathbb{R}^{x \times y}$ indicates $r_n$ samples from the nth class where $\sum_{i=1}^{n} y_i = y$ [9]. Assume $g \in \mathbb{R}^{x \times 1}$ is the test sample and use n sample classes to classify the test model with a marginal restoration error. The philosophy of a SDC can be fulfilled by improving the importance of non-linear transformation among the test sample and the class sample. Therefore, SDC be able to be defined in Eq. 4 and 5 as follows

$$h(p) = \arg \max p_i$$

$$h(p) = \arg \max \log \left( \sum_{i=1}^{n} \exp\left( -\lambda ||p - p_i||_2 \right) \right)$$

where $h(p)$ postulates the particular distance from the test sample to the $i$th class $\lambda > 0$ to have a penalty cost. Hence if $p$ identifies to the $i$th class, then $p$ and $p_i$ would have likely same characteristics and so $||p - p_i||_2$ is progressing close towards zero and hence maximizing $z_i$ can achieve the highest potential value in an asymptotic way.

5. Results and Discussions

For the detection of the epilepsy, in this paper we have used the Haar, dB2, dB8 and Sym8 wavelet features and the Softmax Discriminant Classifier is employed in this work. The Performance parameters

| Patient | Haar | dB2 | Sym8 | dB4 |
|---------|------|-----|------|-----|
| 1       | 21.59| 13.94| 13.94| 17.58|
| 2       | 13.94| 13.94| 15.47| 19.25|
| 3       | 14.45| 17.58| 21.60| 16.37|
| 4       | 21.59| 21.60| 21.60| 21.60|
| 5       | 23.08| 14.64| 23.08| 23.08|
| 6       | 23.08| 18.75| 23.08| 23.08|
| 7       | 14.45| 13.97| 15.47| 18.75|
| 8       | 16.00| 23.08| 18.75| 23.08|
| 9       | 13.97| 13.94| 13.94| 13.33|
| 10      | 21.59| 14.64| 16.67| 14.64|
| 11      | 13.97| 13.94| 13.94| 13.94|
| 12      | 23.08| 23.08| 23.08| 23.08|
| 13      | 21.59| 21.60| 21.60| 21.60|
| 14      | 13.97| 13.94| 13.94| 13.94|
| 15      | 23.08| 14.64| 23.08| 23.08|
| 16      | 21.43| 13.33| 18.75| 14.64|
| 17      | 20.00| 18.75| 23.08| 23.08|
| 18      | 14.45| 23.08| 13.97| 13.94|
| 19      | 14.64| 18.75| 23.08| 23.08|
| 20      | 13.94| 13.94| 15.47| 19.25|
The performance index, accuracy, sensitivity, specificity, time delay and quality values of the average results of 20 patients are proposed in Eqs. 6 to 9 and analysed in Table 2 respectively.

**Performance Index (PI)**

\[
PI = \frac{PC-MC-FA}{PC} \times 100
\]  
(6)

Where **PC** – Perfect Classification, **MC** – Missed Classification and **FA** – False Alarm.

**Sensitivity (Sen)**

\[
Sen = \frac{PC}{PC+FA} \times 100
\]  
(7)

**Specificity (Spec)**

\[
Spec = \frac{PC}{PC+MC} \times 100
\]  
(8)

**Accuracy**

\[
Accuracy = \frac{Sen + Spec}{2} \times 100
\]  
(9)

| Table 2. Average Performance measures of SDC Classifier for all wavelets |
|---------------------------------------------------------------|
| Parameters          | Haar  | db2  | Sym 8 | db4  |
|---------------------|-------|------|-------|------|
| Perfect Classification (%) | 79.23 | 75.14 | 81.87 | 79.45 |
| Missed Classification (%) | 7.59  | 10.07 | 5.89  | 6.77  |
| False Alarm (%)      | 13.17 | 14.79 | 12.24 | 13.80 |
| Performance Index (%) | 68.70 | 59.59 | 72.61 | 67.14 |
| Sensitivity (%)      | 86.82 | 85.21 | 87.86 | 86.20 |
| Specificity (%)      | 92.41 | 89.93 | 94.11 | 93.26 |
| Accuracy (%)         | 89.62 | 87.57 | 90.93 | 89.73 |
| Time Delay (Seconds) | 2.04  | 2.11  | 1.99  | 1.99  |
| Quality Values       | 18.02 | 17.47 | 18.87 | 18.50 |

Figure 2 demonstrates the study of time delay and quality value, where the wavelet features as a feature extraction technique are accompanied by the Softmax Discriminant Classifier. The time delay is not persistent as it diverges against quality values in an abrupt manner throughout.

![Time Delay and Quality Values](image)

**Figure 2 Time Delay and Quality Value Analysis**

The figure 3 shows the Analysis of Performance index and Accuracy using the sym8 wavelet feature trailed by the Softmax discriminant classifier.
Figure 3 Performance Index and the Accuracy measures of Sym8 Wavelet feature followed by the SDC Classifier.

Thus by taking into account the Wavelet features for the feature extraction technique, this paper provides the performance analysis and the Softmax discriminant classifier serves as the classifier for the detection of epilepsy from the EEG signals. The two parameters used to measure the classifiers performance are the quality values and performance index. Better accuracy is given by the sym8 wavelet with the SDC classifier, among other wavelet features. The average perfect classification is estimated to be 81.87 %, average efficiency index is 72.61 %, and the average of the specificity and sensitivity values are given as 94.11 % and 87.86 % respectively. The average quality value of sym8 is 18.87 and the average time delay achieved is 1.99 seconds and 90.93 % is the average accuracy achieved. The use of the dimensionality reduction technique trailed by the post classifier for the detection of epilepsy could be included in future work.

6. References
[1] Hussain, L., Aziz, W., Khan, A.S., Abbasi, A.Q. and Hassan, S.Z., 2015. Classification of electroencephalography (EEG) alcoholic and control subjects using machine learning ensemble methods. J Multidiscip Eng Sci Technol, 2, pp.126-131.
[2] Harikumar, R., Vijayakumar, T. and Sreejith, M.G., 2011, September. Performance analysis of SVD and support vector machines for optimization of fuzzy outputs in classification of epilepsy risk level from EEG signals. In 2011 IEEE Recent Advances in Intelligent Computational Systems (pp. 718-723). IEEE.
[3] Dingle, A.A., Jones, R.D., Carroll, G.J. and Fright, W.R., 1993. A multistage system to detect epileptiform activity in the EEG. IEEE Transactions on Biomedical Engineering, 40(12), pp.1260-1268. Subasi, A 2007, ‘EEG signal classification using wavelet feature extraction and a mixture of expert model’, Expert Systems with Applications, vol. 32, pp. 1084-1093.
[4] Harikumar, R., Vijayakumar, T., Babu, C.G. and Sreejith, M.G., 2013. Performance Analysis of Wavelet Transforms and Principal Components as Post Classifier for the Classification of Epilepsy Risk Levels from EEG Signals. In Proceedings of the Fourth International Conference on Signal and Image Processing 2012 (ICSIP 2012) (pp. 25-35). Springer, India.
[5] Deepa, R., Shanmugam, A. and Tamilselvan, E., 2017. EEG Feature Extraction and Classification of Alzheimer’s Disease using Support Vector Machine Classifier, International Journal of Electronics, Electrical and Computational System, vol. 6(8), pp. 165-169.
[6] Amin, H.U., Malik, A.S., Ahmad, R.F., Badruddin, N., Kamel, N., Hussain, M. and Chooi, W.T., 2015. Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques. Australasian physical & engineering sciences in medicine, 38(1), pp.139-149.
[7] Deepa R, Shanmugam A and Sivasenapathi B, “Reasoning of EEG Waveform using Revised Principal Component Analysis (RPCA)”, Biomedical Research, Volume 28, issue 9, May 2017.
[8] Zhao, J., Zhou, W., Liu, K. and Cai, D., 2011. Application of SVM and wavelet analysis in EEG classification. Sheng wu yi xue gong cheng xue za zhi = Journal of biomedical engineering = Shengwu yixue gongchengxue zazhi, 28(2), p.277.
[9] Rajaguru, H. and Prabhakar, S.K., 2017, July. Softmax discriminant classifier for detection of risk
levels in alcoholic EEG signals. In 2017 International Conference on Computing Methodologies and Communication (ICCMC) (pp. 989-991). IEEE.