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Detection of Epileptic Seizures using ANN and SVM

Dhairya Singh[1], Purva Singh[2], Gautam Kumar[3]

[1,2,3]M.Tech, Communication Engineering, Galgotias University, Greater Noida

Abstract: **Electroencephalography signal is the recording of electrical activity of brain that provides valuable information of the brain function and neurological disorder. This thesis proposed artificial neural network and support vector machine for classification of EEG signals. The study on characterization of epileptic Seizure EEG signals was carried out to address the need for an automatic system to allow timely medical intervention using advanced methodology.**

1. INTRODUCTION

Human Brain is the most advanced organ among all the systems in the human body, conjointly the most remarkable one. It exhibits rich spatiotemporal dynamics. In medical terms, human brain is additionally referred to as an encephalon and the medical technique that reads scalp electrical activity of the encephalon is called ELECTROENCEPHALOGRAPH (EEG). The EEG was initially measured in humans by Hans Berger in 1929 [1]. EEG is the recording of electrical activity along the scalp, produced by the firing of neurons within the brain. The EEG is a highly complex signal & among the foremost common sources of information used to study brain function and neurological disorders [2]. It consists of electrical rhythms and transient discharges that are discriminated by location, frequency, amplitude, form, periodicity, and useful properties [1]. The EEG is a non-invasive, non-linear, complex & non-stationary signal that is generated due to activation of millions of neurons. A non-stationary signal is one whose statistical properties like mean & variance do not remain constant over time [3].

1.1 Epilepsy

Epilepsy, a malady far-famed from earlier period, is now considered the most common disorders of the nervous system [4]. The Greek physician Hippocrates was the first one to acknowledge that it was a disease of the brain and tried to treat it in and of itself. Until the 1800s, non-secular beliefs avoided systematic & scientific investigations in epilepsy. Epilepsy is now regarded as a window to the brain's function and therefore, has become an increasingly active, interdisciplinary field of research [4]. It's second to stroke, and affects about 1% of the world's population [5]. While epilepsy occurs in all age groups, the highest incidences occur in infants and in the aged [6]. The high incidence of epilepsy occurs as a result of a large number of causes, including genetic abnormalities, developmental irregularity, febrile convulsion, as well as brain insults such as craniofacial distress, infections of central nervous system, hypoxia, ischemia and tumors. The hallmark symptoms of epilepsy are recurrent seizures. The seizures are due to sudden development of synchronous neuronal firing in the cerebral cortex and are recorded by electrodes on or inside the brain. EEG is the recording of the electrical activity of the brain. To study the brain's electrical activity, through the electroencephalographic records, is one of the most important tools, which are simple and inexpensive for the diagnosis of neurological diseases. EEG analysis of brain function plays a major role in the diagnosis, discrimination and management of brain diseases like epilepsy, brain tumors and brain disorders.

1.2 Seizure

A seizure is an involuntary alteration in behavior, movement, sensation, or consciousness ensuing from abnormal neuronal activity in the brain. In the case of epilepsy, a malfunctioning region of the brain or the dysfunction of a biochemical mechanism causes the abnormal neuronal activity. This is often in distinction to non-epileptic seizures, which are a response to a disturbance external to the central nervous system such as alcohol withdrawal, drug abuse, acute sickness, or sleep deprivation.

2. WAVELET TRANSFORM

Spectral analysis of brain activity was limited to signals without major temporal changes or that are slowly changing with time. With the development of signal processing techniques, it becomes easier to deal with non-stationary signals. Time-frequency analysis is a more general approach to study spontaneous or evoked brain activity than temporal or spectral analysis alone. The wavelet transform is an effective tool in signal processing due to its attractive properties such as time-frequency localization. The Fourier Transform is probably the most popular transform used to obtain the frequency spectrum of a signal. But the Fourier Transform is suitable for stationary signals only. The Fourier Transform, informs how much of each frequency exists in the signal, it does not tell at which time these frequency components occur. Signals such as image and speech have different characteristics at different time or space, i.e., they are non-stationary. Most of the biological signals such as, Electrocardiogram, Electromyogram, etc. are non-stationary. To analyze these signals, both time and frequency information are needed simultaneously, which means a time-frequency representation of the signal is needed. To solve this problem, the Short-Time Fourier Transform (STFT) was introduced. The major drawback of the STFT is that it uses a fixed window width. The Wavelet Transform, which was developed in the last two decades, provides a better time-frequency representation of the signal than any other existing transforms. In Wavelet Transform, as frequency increases, the time resolution increases; similarly, as frequency decreases, the frequency resolution increases [7].

The main advantage of wavelet transform (WT) in the analysis of EEG signals is that it allows accurate decomposition of a neuroelectrical record into a set of component waveforms. These detail functions can isolate all scales of waveform structure from the largest to smallest pattern of variation all in time and space that is available in the signal [8].

In wavelet transform, a signal *x(t)* which belongs to the square integrable subspace L^2 (R) is expressed in terms of scaling function $\phi_{j,k}(t)$ and mother wavelet function $\psi_{j,k}(t)$. Here *j* is the parameter of dilation or the visibility in frequency and *k* is the parameter of the position.

$$x(t) = \sum_k a_{j_0,k}\phi_{j_0,k}(t) + \sum_{j=j_0}^{\infty}\sum_k d_{j,k}\psi_{j,k}(t) \quad (1.1)$$

Where *a, d* are the coefficients associated with $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ respectively. The coefficients *a, b* can be calculated as we calculate the coefficients in Fourier transform. The expression of *a, b* are given in the following equations

$$a_{j_0,k} = \int_{-\infty}^{\infty} x(t)\phi_{j_0,k}(t)dt \quad (1.2)$$

$$d_{j_0,k} = \int_{-\infty}^{\infty} x(t)\psi_{j_0,k}(t)dt \quad (1.3)$$

2.1 Multi-Resolution analysis using filter banks

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up-sampling and down-sampling (sub-sampling) operations. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in Figure 1. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time multi resolution to discrete-time filters. In the figure 1, the signal is denoted by the sequence x[n], where n is an integer. The low pass Filter is denoted by G_0 while the high pass filter is denoted by H_0. At each level, the high pass filter produces detail information d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n]. At each decomposition level, the half band filters produce signal spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half.

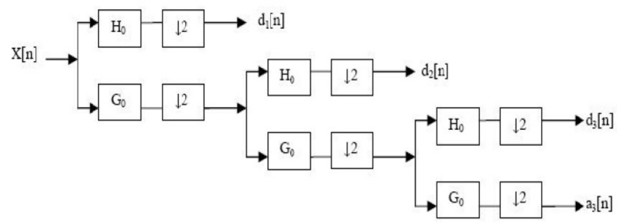

Figure 1.Three-level wavelet decomposition tree.

3. ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network (ANN) is an information processing system that has sure performance characteristics in common with biological neural networks. Artificial Neural Networks are developed as generalizations of mathematical models of human cognition or neural biology. A Neural Web consists of an oversized variety of simple processing elements called neurons or nodes. Each neuron is connected to other neurons by means of directed communication links, with an associated weight. Neural Nets can be applied to issues like storing, recalling data/patterns, classifying patterns, performing general mapping from input to output patterns. Each neuron has an internal state, called its activation (activity level) which is a function of the inputs it has received. Typically, a neuron sends its activation as a signal to several other neurons that computes the overall output of the neural network.

ANNs are a highly interconnected and simple processing unit which is designed to model the way human brain performs a particular task [9]. Each unit is called a neuron. It forms a weighted sum of its inputs and a constant term called bias is added. This sum is passed through a transfer function such as linear, sigmoid or hyperbolic tangent. In the construction of neural architecture, the choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems. In order to find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions [10].

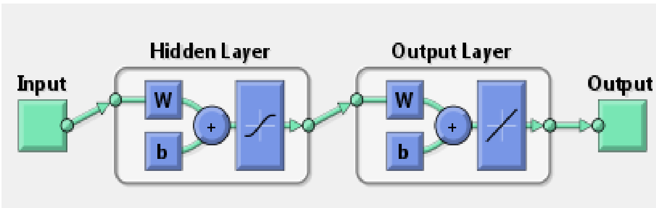

Figure 2: Neural network architecture

4. SUPPORT VECTOR MACHINE

The support vector machine was developed in the 1995 by C.Cortes & V.Vapnik [11]. SVM is a new kind of classifier that's motivated by two ideas. First, transforming data into a high dimensional space can transform complex issues (with complex decision surfaces) into simpler problems that can use linear discriminant functions. Second, SVMs are motivated by the concept of training and using only those inputs that are near the decision surface since they provide the foremost vital information about the classification. It's a form of learning machine based on statistical learning theory. The basic fact of applying SVM to pattern classification is stated as follows: initially the input vectors are mapped into one features space, possible in higher space, either linearly or nonlinearly, which is relevant with the kernel function. Then, within the feature space from the first step, optimized linear division, is sought i.e. a hyper plane is constructed which separates two classes. It can be extended to multi-class. SVMs training always seek a global optimized solution and avoid over fitting, so it has ability to deal with an over-sized range of feature [12].

5. DATA SELECTION

The data used was made available by Bonn University for research purposes & is described in Andrzejak et al [13]. In this section, we restrict ourselves to only a short description and refer to Andrzejak et al. (2001) for further details. The complete data set consists of five sets (denoted A–E) each containing 100 single channel EEG segments. These segments were selected and cut out from continuous multi-channel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. Sets A and B consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme. Volunteers were relaxed in an awaken state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E originated from EEG archive of pre-surgical diagnosis. EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. While sets C and D contained only activity measured during seizure free intervals, set E only contained seizure activity. Here segments were selected from all recording sites exhibiting ictal activity. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12 bit resolution. Band-pass filter settings were 0.53– 40 Hz (12dB/oct). In this study, the complete dataset (A, B, C, D and E) has been used.

6. WAVELET FEATURE EXTRACTION

For analysis of EEG signals using discrete wavelet transform, selection of the appropriate wavelet and number of decomposition level is important. The decomposition levels are picked depending upon main frequency components of the signal [14]. In the present work, daubechies wavelet of order 2 and 4 level of decomposition is used for computation of wavelet coefficients. The wavelet used here has smoothing characteristics which makes it suitable to detect changes in the EEG signal. Each of the EEG signals is decomposed into four detail wavelet coefficients (D1, D2, D3, and D4) and one approximation wavelet coefficients (A4). The representation D1, D2, D3, and D4 refers to the coefficients obtained at first, second, third and fourth level respectively. The total 265 wavelet coefficients are computed for each EEG segment in which 247 are the detail coefficients (129 + 66 + 34 + 18) and 18 are the approximation coefficient. The dimension of the features obtained from DWT method is large. So different statistics methods are used to reduce the number of features are:-

i) Maximum of wavelet coefficients in each sub band

ii) Minimum of wavelet coefficients in each sub band

iii) Mean of wavelet coefficients in each sub band.

iv) Standard Deviation of wavelet coefficients in each sub band.

The computed detail and approximation wavelet coefficients of the EEG signals were used as the feature vectors representing the signals. The EEG signals were decomposed into time-frequency representations using DWT and statistical features were calculated to depict their distribution. Therefore, the 4 coefficients are obtained from each of the 5 sub bands resulting in a total of 20 coefficients feature vector as shown in Table 1.

7. RESULT

The statistical features like Mean, Standard Deviation, Maximum and Minimum of the coefficients, was extracted for daubechies wavelet of order 2 and level 4. The extracted features for first frame from five classes are shown in table below

Table 1. Features for first frame from five classes.

Data Set	Featu-res	Wavelet Sub bands				
		D1	D2	D3	D4	A4
Set A	Max	21.03	31.30	75.77	120.0	192.6
	Min	-12.0	-42.0	-92.3	-105.3	-172.4
	Mean	-0.26	0.178	1.602	2.170	34.413
	S.D	4.969	14.842	41.187	60.347	96.462
Set B	Max	14.14	46.928	102.26	120.79	302.98
	Min	-14.7	-51.48	-139.1	-163.7	-208.9
	Mean	0.472	0.0892	-7.327	-31.60	24.045
	S.D	6.048	17.938	60.055	73.929	146.46
Set C	Max	6.597	23.87	44.348	88.247	320.45
	Min	-7.33	-20.50	-30.92	-89.15	-175.7
	Mean	-0.09	-0.018	1.6568	-2.636	94.158
	S.D	2.921	8.7319	19.455	43.635	126.36
Set D	Max	6.407	17.196	49.523	142.37	231.6
	Min	-7.37	-21.11	-42.63	-182.4	-269.4
	Mean	0.066	-0.135	2.2645	-12.34	-39.06
	S.D	2.800	9.5142	25.913	95.077	153.39
Set E	Max	258.0	644.36	1524.4	1420.1	1639.2
	Min	-325	-1074	-1508	-1107	-1917
	Mean	-0.13	0.105	65.561	-77.23	281.40
	S.D	75.14	303.67	716.08	614.26	1138.5

7.1 Classification using ANN

Accuracy = Number of correct decisions / Total number of cases
Sensitivity = Number of true positive decisions / Number of actually positive decisions
Specificity = Number of true negative decisions / Number of actually negative decisions

Table 2. Results using ANN

Parameters	Result (%)
Accuracy	96.00
Sensitivity	100.00
Specificity	90.00

7.2 Classification using SVM

Table 3. Results using SVM

Parameters	Result (%)
Accuracy	85.06
Sensitivity	86.66
Specificity	84.44

8. CONCLUSION

The present works aim at classifying the EEG pattern into five groups, based on the area of the frequency spectrum under different sub-bands. After feature extraction, the classification of the patterns based on the frequency spectrum features is carried out using a neural network and support vector machine. The network based on the back-propagation algorithm is able to achieve an accuracy of 96.00% and the radial basis function support vector machine is able to achieve an accuracy of 85.06%. Comparison result shows that the performance of ANN classifier is superior to SVM classifier. The performance of the proposed combination of methods with feature extraction can be relied on and this combined method uses very few inputs and can be used to forecast the subject's seizure in real time, and also may be considered as an expert's opinion on the issue.

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