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Detection of Epileptic Seizure

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***Abstract*— Epileptic seizure is a transient symptom of abnormal excessive or synchronous neuronal activity in the brain. Epilepsy is one of the most serious neurological disorder. About 50 million people worldwide are suffering from epilepsy and 85% of those live in the developing countries. Detection of epileptic seizure could be very useful for the patient safety. EEG has been considered as a successful tool in neuroscience to diagnose diseases and disorders. Various methods have been proposed to detect the onset of seizure. The main objective is to detect the seizure with higher sensitivity, specificity and accuracy. In the proposed algorithm the signal is filtered into 5 consecutive sub-bands using band pass filter then various features are extracted from each sub-band and then the classifiers back propagation network and support vector machine are used separately to detect the seizure onset. The output of both the classifiers are then compared to find which classifier provides better performance. The experimental result shows that the proposed method effectively detects the seizure onset in EEG signal and also showed a reasonable accuracy in detection.**

Keywords— Electroencephalography (EEG), Seizure, signal complexity, signal mobility, fractal dimension, Hurst exponent, Back propagation network (BPN) Support vector machine (SVM).

I. INTRODUCTION

Epilepsy is one of the most chronic neurological disorders with a prevalence of approximately 1% of the world's population [9]. It is the most prevalent brain disorder among adults and children, second to stroke. The word 'epilepsy' is derived from the Greek word epilambanein, which means 'to seize or attack'. The International league against epilepsy defines epileptic seizure as a transient occurrence of signs and symptoms due to abnormal excessive or synchronous neuronal activity in the brain' [10]. Hence, seizure are the result of sudden, usually brief, excessive electrical discharges in a group of brain cells and that different parts of the brain can be the site of such discharges.

Epileptic seizures may be associated with impaired consciousness, at times violent body movements or rhythmic jerks with potential increasing risk of injury, or even death. One particular disabling aspect of seizures is their sudden and unpredictable nature, limiting patient's activities and resulting in the sense of helplessness. The common treatments for epilepsy is medication and surgery but it also fails to satisfactorily control seizure [11].

Epileptic seizures are divided by their clinical manifestation into focal or partial, generalized, unilateral and unclassified seizure [1]. Focal epileptic seizures involve only in the part of the central hemisphere and produce symptoms in corresponding parts of the body or in some related mental functions.

Generalized epileptic seizures involve the entire part of brain and produce bilateral motor symptoms usually with loss of consciousness. Both types of epileptic seizures can occur at all ages. Generalized epileptic seizures can be subdivided into absence (petit mal) and tonic-clonic (grand mal) seizures (James, 1997).

Seizure consists of four states namely Inter-ictal, Pre-ictal, Ictal, Post- ictal. The Inter-ictal state refers to the time period between the seizures and it shows occasional transient waveform as either isolated peaks, spike trains, sharp waves or spike wave complexes. The spike last between 20 and 70msec. Pre-ictal state refers to the state before the ictal state. Ictal state refers to the seizure state and it is composed of a continuous discharge of polymorphic waveforms of variable amplitude and frequency, spike and sharp wave complexes (3/sec) and phantom spikes (<50μV). Post-ictal state refers to the state shortly after the ictal state. It shows a focal slowing.

Automatic analysis of EEG recordings for assisting in the diagnosis of epilepsy started early in 1970s. Seizure detection techniques can be divided into five categories: time domain based, frequency domain based, time-frequency domain based, artificial neural network based and nonlinear methods [2]. In recent years there are various experiments and results published for epileptic seizure. Various feature extraction methods are used, such as wavelet coherence, Empirical mode decomposition [4], chaos analysis [5], statistical methods and Lyapunov exponents [6] to detect seizure. The EEG spectrum contains some characteristic waveforms that fall primarily within five frequency bands – delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-60 Hz).

In this paper, the EEG sub bands are extracted from signal using band pass filter and then the signal segmentation is performed. Then the features are extracted from each sub-band and then the signal is classified using artificial neural network (ANN). The detailed description of proposed method is given in section II

II. MATERIALS AND METHODS

A. Proposed method

Outline of the proposed seizure detection algorithm is shown in fig. 1. In this algorithm, the EEG signal is band pass filtered to yield sub-bands of interest and then it is segmented into 2-second epoch with overlapping. Then the statistical and complexity features are extracted from each sub-band and it is classified using classifiers. The proposed method is specified in the following sections

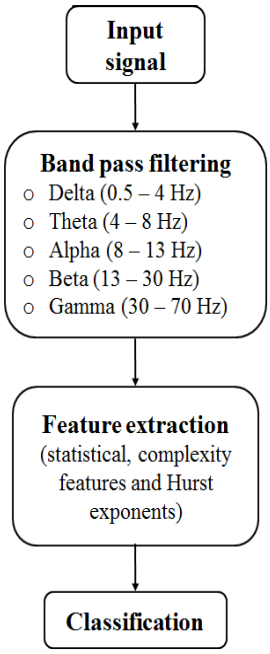

Fig. 1. Block diagram of proposed system

B. EEG database

The data set used in the paper is publicly available online by Dr. Ralph Andrzejak of the epileptic center at the University of Bonn, Germany [3]. The complete data set consists of five sets (denoted A-E) each containing 100 single EEG segments of 23.6 sec duration.

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 awake state with eyes open (A) and eyes closed (B), respectively. Sets C, D, E originated from EEG archive of pre surgical diagnosis. The 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, 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.

All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. After 12 bit analog-to-digital conversion, the data were written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. In this paper, we used two dataset (C and E) having data with seizure free interval and with seizure activity.

C. Band pass filtering and segmentation

The sampling frequency of the EEG signal is 173 Hz. Hence, according to the Nyquist sampling theorem, the maximum useful frequency is half of the sampling frequency i.e. 86.5 Hz. The signal is decomposed into desired sub-bands: delta (.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-70 Hz) using band pass filter. The filter used here is Butterworth band pass filter of order 2. The filtered sub-bands of both normal and seizure signal are shown in fig. 2 and fig. 3

Segmentation is done by taking the moving window of length 2 sec with 50% overlapping. The size of the window is chosen small in order to captivate the sudden nature of seizure activity.

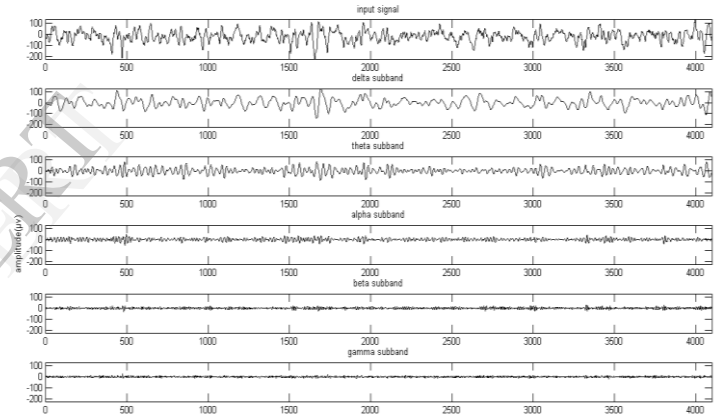

Fig.2. Normal EEG signals with its sub-bands

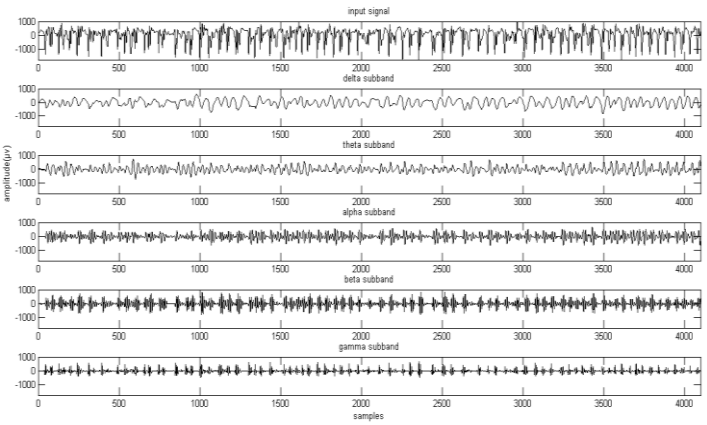

Fig.3. Seizure EEG signals with its sub-bands

D. Feature extraction

The features are calculated from each EEG segment. The purpose of feature extraction is to reduce the dimension of original data by measuring certain features that distinguish one input pattern from another.

The features that are extracted here to detect seizure are: mean, variance, standard deviation, fractal dimension, signal complexity, signal mobility and Hurst exponents. The detail description of each feature is given below

1) Mean

Mean is the average value of the signal. It is indicated by μ. The mean can be expressed as in Eq.1,

$$\mu = \frac{1}{N}\left(\sum_i (X_i(n))\right) \quad (1)$$

where, N is the number of samples and $X_i(n)$ is the amplitude of each i^{th} sample

2) Variance

This parameter, variance describes how far the signal amplitudes lie from the mean (μ). It is found that the variance is higher for seizure signals when compared to normal signals.

Let us assume a random variable X that have the sample values of each EEG sub-band signal. Let the sample value of X be $X_i=\{X_1, X_2 \ldots Xn\}$. where, i represents any one of the sample set from the sub-bands. The variance can be expressed as in Eq. 2,

$$\sigma^2 = \frac{1}{N}\left(\sum_i (X_i(n) - \mu)^2\right) \quad (2)$$

where, N is the number of samples in the signal

3) Standard deviation

The standard deviation is similar to the average deviation. This is achieved by squaring each of the deviation before taking the average. Standard deviation is given in Eq.3,

$$\sigma = \sqrt{\frac{\sum_i ((X_i-\mu)^2)}{(N-1)}} \quad (3)$$

where, μ is the mean of set X and N is the number of samples

4) Fractal dimension

It is a measure that quantitatively assesses the self-similarity of a signal.

Among all the fractal - based complexity measures, the Higuchi algorithm is one of the most accurate and efficient methods to estimate self-similarity.

From the time-series X with N points, first a set of K sub-series with different resolution are formed. The new time series X_k is defined as shown in Eq.4,

$$X_k^m : x(m), x(m+k), x(m+2k), \ldots, x\left\{m+\left[(N-m)/k\right]k\right\} \quad (4)$$

where, m indicates the initial time indices (m = 1, 2,... k), k indicates the discrete time interval between points(delay). For each of the time series X_k^m constructed, the average length $L_m(k)$ is computed as given in Eq.5

$$L_m(k) = \frac{\left[\sum_{i=1}^{\left[\frac{N-m}{k}\right]} |x(m+ik) - x(m+(i-1)k)|(N-1)\right]}{\left(\left[\frac{N-m}{k}\right]\right)k} \quad (5)$$

where, N is the total length of the data sequence X and $(N - 1) / [(N-m)/k]$ and k is a normalization factor

An average length is calculated as the mean of the k lengths $L_m(k)$. This procedure is repeated for each K ranging from 1 to K_{max} yielding a sum of average lengths $L(k)$ for each k as indicated in Eq.6

$$L(k) = \sum_m L_m(k),\ m = 1, 2, .., k \quad (6)$$

The total average length for scale k, $L(k)$, is proportional to k^{-D} where, D is the fractal dimension by Higuchi's method. The curve is plotted for ln $(L(k))$ versus ln (k) and the slope of the curve is estimated which is the estimate of fractal dimension.

5) signal mobility and complexity

It quantitatively measures the level of variations along the signal. It is often used in analysis of biomedical signal to quantify the 1st and 2nd order variation in the signal.

Signal mobility addresses the normalized 1st order variation of the signal and it represents the mean frequency of the signal.

Signal complexity deals with the normalized 2nd order variation of the signal. And it represents the change in frequency.

Let us consider the variable X_i to represent the signal. Where $i = 1, 2 \ldots N$

Let d_i represent the vector of 1st order variation of the signal as shown in Eq.7, Where $i = 1, 2 \ldots N$-1

$$d_i = X_i - X_{i-1} \quad (7)$$

Let g_i represent the vector of 2nd order variation of the signal as shown in Eq.8, where $i = 1, 2 \ldots N$-2

$$g_i = d_i - d_{i-1} \quad (8)$$

TABLE.1. FEATURE VALUES OF NORMAL AND SEIZURE SIGNAL

Signal	**Normal signal**					**Seizure signal**				
Features	*Delta*	*Theta*	*Alpha*	*Beta*	*Gamma*	*Delta*	*Theta*	*Alpha*	*Beta*	*Gamma*
Mean	-0.0283	0.0076	-0.0039	0.0022	-0.0009	0.562	0.3732	-0.2548	0.0345	0.0698
Variance	1502.2	643.28	136.78	48.352	21.177	71956	50888	47805	60993	18278
Standard deviation	37.996	24.706	11.547	6.9247	4.5953	266.1	223.33	217.26	246.43	134.75
Fractal dimension	1.2028	1.5359	1.8077	1.8992	1.8490	1.193	1.5370	1.7858	1.8491	1.9464
Signal mobility	0.0948	0.2025	0.3444	0.5417	0.7649	0.121	0.216	0.4107	0.5595	0.6760
Signal complexity	0.1391	0.1092	0.1665	0.2116	0.8178	0.178	0.1877	0.1530	0.1688	0.4373
Hurst exponents	0.6247	0.7161	0.7585	0.7999	0.7535	0.668	0.7225	0.7787	0.8133	0.8038

Then the fundamental first and second order factors are defined using x, d and g in Eq. 9, 10 and 11,

$$S_0 = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}},\ i = 1,2..N \quad (9)$$

$$S_1 = \sqrt{\frac{\sum_{i=2}^{(N-1)} d_i^2}{N-1}},\ i = 1,2..N\text{-}1 \quad (10)$$

$$S_2 = \sqrt{\frac{\sum_{i=3}^{(N-2)} g_i^2}{N-2}},\ i = 1,2..N\text{-}2 \quad (11)$$

Hence the signal mobility and complexity are defined as in Eq.12 and 13,

$$signal\ mobility = \frac{S_1}{S_0} \quad (12)$$

$$signal\ complexity = \sqrt{\left(\frac{S_2^2}{S_1^2}\right) - \left(\frac{S_1^2}{S_0^2}\right)} \quad (13)$$

6) Hurst exponents

The Hurst exponent is a numerical estimate of the predictability of a time series. It is defined as the relative tendency of a time series to either regress to a long term value in a direction. Hurst exponent (H) is used to describe a fractal self-affine object, because it indicates the level of roughness of curves. H is used to determine if a temporal series has a fractal behavior and it measures the intensity of dependence [7]. When H = 0.5 the analyzed phenomena is random (Brownian noise). When 0.5<H<1 it is persistent and when 0<H<0.5 it is anti-persistent.

The Hurst exponent can be calculated by the following steps given below:

a) Calculate the mean as in Eq.14,

$$m = \frac{1}{N}\sum_i X_i, i = 1,2,\ldots,N \quad (14)$$

b) Calculate the mean adjusted series as in Eq.15

$$y_t = X_t - m, t=1,2,\ldots,N \quad (15)$$

c) Calculate the cumulative deviate series as in Eq.16

$$Z_t = \sum_i y_i,\ t = 1, 2,..,N \quad (16)$$

d) Compute the range as in Eq.17

$$R(N) = max(Z_1, Z_2, \ldots, Z_N) - min(Z_1, Z_2, \ldots, Z_N) \quad (17)$$

e) Compute the standard deviation as in Eq.18

$$S(N) = \sqrt{\frac{\sum_i (x_i - m)^2}{N}},\ i = 1,2,..,N \quad (18)$$

f) Calculate the rescaled range and average over all the partial time series of length N as in Eq.19,

$$\left(\frac{R_t}{S_t}\right),\ t = 1, 2,\ldots, N \quad (19)$$

The Hurst exponent is estimated by fitting the power law to the data. This can be done by plotting the log (R_t / S_t) as a function of log *(n)* and fitting a straight line and the slope of the line gives the value of H.

The above said feature values for one normal signal and one seizure signal are given in table 1

E. Classification

Classification task to be handled in this study is to distinguish between normal and the ictal state of EEG signals

using the extracted features. Here, the BPN and SVM are employed to manage the binary classification task.

Back propagation is a systematic method for training multi-layer artificial neural networks. It is multi-layer feed forward network using extend gradient descent based delta-learning rule, commonly known as back propagation rule.

It provides a computationally efficient method for changing the weights in a feed forward network, with differentiable activation units, to learn a training set of input-output. It minimizes the total squared error of the output computed by the net. The network is trained by supervised learning method. The aim of the network is to train the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the input that are similar.

In this paper the back propagation network is set with log sigmoid as the activation function. The network consists of 35 input nodes, one hidden layer consisting of 71 neurons and 2 output nodes. The network architecture is shown in fig.4

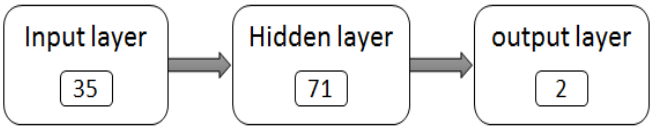

Fig.4. Neural Network architecture

The data is separated into two kinds for classification: one is training vector and other is testing vectors. For training vector 80% data i.e., 160 signals (80 normal and 80 seizure signals) and for testing vectors 20% data i.e., 40 signals (20 normal and 20 seizure signals) are included.

To compare the performance of BPN, SVM is used. SVM is a pattern recognition technique which attracts remarkable attention in biomedical signal applications. The goal of the SVM is to produce a model (based on the training data) to classify the test data. SVM can classify data separated by linear and non-linear boundaries. Through the kernel functions, the problem is implicitly mapped to a higher dimensional space in which hyper planes suffice to define boundaries. It is also capable of classifying the over lapping and non-separable data.

A penalty is assigned for input data that fall on the wrong side of the hyper planes, and an optimal decision is found. It maps the input vectors to a higher dimensional space where a maximal separating hyper plane is constructed. Here, the kernel function 'linear' is used to separate the data by a hyper plane. The data for classification in SVM is also divided into training and testing vectors. The training vector consists of 160 signals (80 normal and 80 seizure) and testing vector consists of 40 signals (20 normal and 20 seizure).

III. RESULTS AND DISCUSSION

The data set consisted a total of 200 (100 seizure and 100 non-seizure) EEG signals sampled at 173 Hz. Initially each EEG signal is band pass filtered to yield the sub-bands of interest namely delta (0.5 – 4 Hz), theta (4 – 8 Hz), alpha (8 – 13 Hz), beta (13 – 30 Hz), gamma (30 – 70 Hz). Then each sub-band is segmented into 2-sec with 50% overlap. Then for each sub-band the features are extracted.

The statistical features namely mean, variance and standard deviation are computed for each sub-band and it showed a significant variation for normal and seizure signals. The statistical features have higher values for seizure signals when compared with the normal signal.

The fractal dimension (FD) is reduced for seizure signals when compared to the normal signal and the value of FD ranges between 1 and 2. The FD is reduced in seizure signals due to the complexity reduction of the brain caused by the reduction in modularity of brain signals.

The signal complexity, mobility and Hurst exponents also show an increase in the seizure signal than the normal signal. The average value of 100 normal and seizure signals are given in Table 3.

Hence, BPN and SVM are trained with features mean, variance, standard deviation, signal mobility, signal complexity and Hurst exponents from each sub-band, totally, consisting of 35 features. The data is divided into training data set and testing data set. 80% of the data is taken as training input data and other 20% is taken for testing.

TABLE.2. AVERAGED FEATURE VALUES OF 100 NORMAL AND SEIZURE SIGNAL

Signal	**Normal signal**					**Seizure signal**				
Features	*Delta*	*Theta*	*Alpha*	*Beta*	*Gamma*	*Delta*	*Theta*	*Alpha*	*Beta*	*Gamma*
Mean	0.6401	-0.0026	0.0154	0.0189	-0.0155	0.591	0.016	0.006	0.0223	0.018
Variance	1844.4	521.43	235.66	114.78	64.333	28939	44200	23829	22072	7562
Standard deviation	39.003	21.207	13.482	9.0410	6.7946	149.5	183.14	131.83	116.01	70.20
Fractal dimension	1.3488	1.6317	1.8153	1.8871	1.9045	1.173	1.552	1.793	1.902	1.965
Signal mobility	0.0866	0.2106	0.3539	0.5605	0.8628	0.145	0.222	0.381	0.552	0.695
Signal complexity	0.1458	0.1310	0.1538	0.2248	0.8050	0.169	0.138	0.156	0.204	0.507
Hurst exponents	0.6175	0.7150	0.7741	0.8226	0.8294	0.663	0.745	0.786	0.804	0.775

The performance of the proposed classifiers is studied using the standard measures such as sensitivity (Sen),

specificity (Spe) and accuracy (Acc) as shown in Eq. 20, 21 and 22

$$Sen = \left[\frac{TP}{(TP+FN)}\right] * 100\% \quad (20)$$

$$Spec = \left[\frac{TN}{(TN+FP)}\right] * 100\% \quad (21)$$

$$Acc = \left[\frac{(TP+TN)}{(TP+TN+FP+FN)}\right] * 100\ \% \quad (22)$$

The values of sensitivity, specificity and accuracy are calculated for both classifiers and are shown in table 3

TABLE 3. RESULTS OBTAINED

PARAMETERS	**BPN**	**SVM**
No. of trained signals	160	160
No. of tested signals	40	40
True positive	18	19
True negative	20	20
False positive	0	0
False negative	2	1
Sensitivity	90%	95%
Specificity	100%	100%
Accuracy	95%	97.5%

IV. CONCLUSION

In this paper, the seizure detection method based on the statistical and complexity features such as mean, variance, standard deviation, fractal dimension, signal mobility, signal complexity and Hurst exponents has been proposed. The EEG signals are decomposed into its sub-bands using band pass filter and then each sub-band is segmented into 2 sec with 50% overlap. After segmentation both the statistical and complexity features are extracted for each segments. The feature vector is computed based on the extracted feature. BPN classifier and SVM classifier is trained with the feature vectors separately and the test data is given to the classifier to detect the seizure signal

It has been shown that BPN provides 90% sensitivity, 100% specificity and 95% accuracy and SVM provides 95% sensitivity, 100% specificity and 97.5% accuracy. Hence, the SVM classifier shows better performance when compared to the other classifier

To better assess the performance of the proposed method, the work will be extended to develop the feature selection techniques for achieving 100% accuracy and the proposed method has to be tested for a set of long-term EEG recordings from large number of patients

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