A NOVEL STATISTICAL APPROACH FOR DETECTION AND CLASSIFICATION OF EPILEPTIC SEIZURES USING DWT AND SVM

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Abstract
In this paper a novel and efficient approach for thresholding and classification of the epileptic and non-epileptic seizures with the aid of statistical features is proposed. The proposed approach initially performs an algebraic interpolation of various normal seizure signals of numerous healthy collections to extract the characteristic, statistical and symptomatic features. An effective feature extraction method for EEG is developed which extracts five synchronous fragments from both training and testing sets and totally 65 features are calculated. Later, the extracted features are subjected to model statistically by aptly amalgamating all these positive features of healthy neural activities to compute a threshold vector which acts as a border of classification between the epileptic and non-epileptic features. Performance of the proposed epileptic classification system is verified with different Machine Learning algorithms like ANN for pattern recognition, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM).The proposed approach is implemented for the Bern-Barcelona EEG database. The comparative simulation results adjudged that SVM classifier provides 95.8333% classification accuracy.

Index Terms: Artificial neural network, Electroencephalogram, K-Nearest Neighbor, Support Vector Machine.

I. INTRODUCTION

Generally, the Human Brain is a very complex and distributed sensory architecture which frequently carries an Electro-Chemical activity resulting in an electric potential in the brain. Electroencephalogram (EEG) can record the electric activity of the human brain by putting an electrodes at appropriate positions in the scalp. EEG has emerged as a most prominent signal source used for diagnosis of many diseases like sleep disorder, epileptic seizure detection, alcoholic consumption measurement etc. In epileptic seizure attack, an abrupt flow of the potential in the brain. For this, a person behaves in abnormal way [1].

Seizures are mainly categorized as two major groups, such as partial epileptic, in which one portion of the brain is affected; whereas the primary generalized epileptic seizure affects the whole brain. A patient affected by epileptic seizure attack has two type of abnormalities in the recording of EEG signal like (i) Interictal (recording between two epileptic seizure attacks). (ii) Ictal (recording during the epileptic seizure) [2]. The abnormal EEG signal has jagged, spiky waves, which also change in amplitude and frequency. The techniques adopted for seizure detection were categorized into many groups like frequency domain analysis, time domain analysis, time-frequency domain analysis, non-linear method analysis, and artificial neural network analysis [3].

A seizure is the consequence of the transient event of signs due to irregular excessive or synchronous neuronal activity in brain [4]. Seizures originate and are sustained in a large neuronal population due to a temporary loss of control over the balance between inhibition and excitation. Since inhibitory mechanisms fail, neurons fire simultaneously at a rate much higher than normal. The abnormal activity might spread to other regions in the brain through pathways which otherwise exist to facilitate normal function. There are different explanations on how a seizure terminates, including the depletion of oxygen supply to the neurons involved in the seizure, and chemical changes which restore the initial imbalance or lack of inhibition [5].

Depending on the brain regions involved in the seizure, the patient may have diverse clinical symptoms. Seizures can affect at least one of the following functions: sensory, motor and autonomic functions; consciousness; emotional state; memory; cognition and behavior. Accordingly, epilepsy has the direct influence on the quality of the life of the epileptic patients. Epilepsy is a disease with a consistently high rate of incidence during the first few months of life. Incidence falls considerably after the first year of life, seems to be relatively stable through the first decade of life, and falls again during adolescence [6, 7]. It is believed that immature brain is more susceptible to seizures since it exhibits increased neuronal excitation and diminished inhibition [8].

Anti-epileptic drugs try to control seizures, however, 30% of patients do not adequately respond and still continue to experience the seizures [9]. In the latter case, other therapies, like surgery, diet, vagus nerve stimulation or responsive neuro-stimulation, can be explored. Nevertheless, the success of these therapies depends on many factors.

A dissimilar EEG pattern is detected during the ictal period containing of rhythmical waveforms for a polyspike activity, wide variety of frequencies, spike and wave complexes, as well as low- amplitude desynchronization [3]. Although interictal findings offer evidence of epilepsy, diagnosis of epilepsy is usually based on observed epileptic seizures [11].In order to detect the epileptic conditions and to identify the epileptic seizure here in this paper we introduced a novel statistical approach for epileptic seizure classification using DWT and SVM analysis.

II. SEIZURE CLASSIFICATION

Perceptive classification of epileptic seizures is a primary footstep for a neurologist towards the correct diagnosis, treatment, and prognostics of the condition, for an engineer knowing the characteristics of these seizures can help in the design of the detection algorithm. The classification of epileptic seizures is still largely based on clinical observation and expert opinions. The International League Against Epilepsy (ILAE) was published a classification system in 1960. Though the 1981 and 1989 updates from the officially accepted classification system, occasionally conceptualization, terminology, and definitions of epilepsy and seizures are updated, modified and improved with the usage of newer multidisciplinary approaches to study epilepsy [12].

There is a two types of abnormal activities of EEG recordings of who suffering from epilepsy, they are inter-ictal and ictal, inter-ictal is the abnormal signals recorded between epileptic seizures and ictal is recorded during an epileptic seizure Fig. 1. The EEG signature of an inter-ictal activity is occasional transient waveforms, as spike trains, isolated spikes, spike-wave complexes or sharp waves. EEG signature of an epileptic seizure (ictal period) is composed of a continuous discharge of polymorphic waveforms of variable amplitude and frequency, spike and sharp wave complexes, rhythmic hyper synchrony, or electro cerebral inactivity observed over a duration longer than the average duration of these abnormalities during inter-ictal periods The introduction of portable recording systems (ambulatory EEG), however, has allowed outpatient EEG recording to become more common.

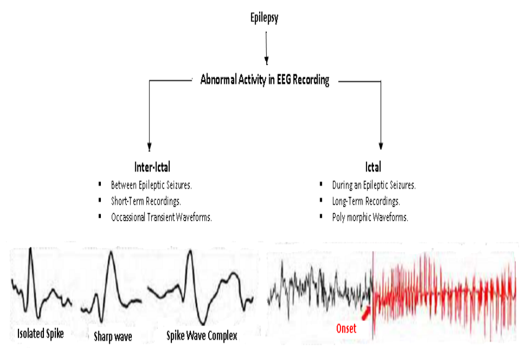

Figure 1. Classification of abnormal activity in the brain.

EEG signals record cerebral electric activities and detect events of epileptic seizures in patients with epilepsy, which afflict approximately 1% of the population [1]. Patients with epilepsy often present in their EEG electrical potentials such as spikes or sharp wave that are of significant diagnostic characteristics.

III. PROPOSED WORK

In this paper, a novel and efficient approach for thresholding and classification of the epileptic and non-epileptic seizures with the aid of statistical features is proposed [13]. The proposed approach is intended centrally for on-time detection and efficient classification of epileptic and non-epileptic seizures. At this stage, we are actually intended to detect the seizures which cause the disorder called epilepsy and we are in a way to develop a generalized framework which can detect and isolate the epileptic seizures from their non-epileptic counterparts when a huge collection of EEG data from numerous patients is tested and analyzed [14].

In order to detect and identify the epilepsies, first of all, we must have an idea of its characteristics which is obtained through a detailed analysis of the characteristics healthy seizure sets. Non-epileptic seizure signals obtained from the EEG collections of healthy persons without epileptic disorder are plotted graphically in Fig. 2, whereas the epileptic seizure signals obtained from the EEG collections of the persons with the epileptic disorder are plotted in Fig. 3 for the Bern-Barcelona EEG database[16].

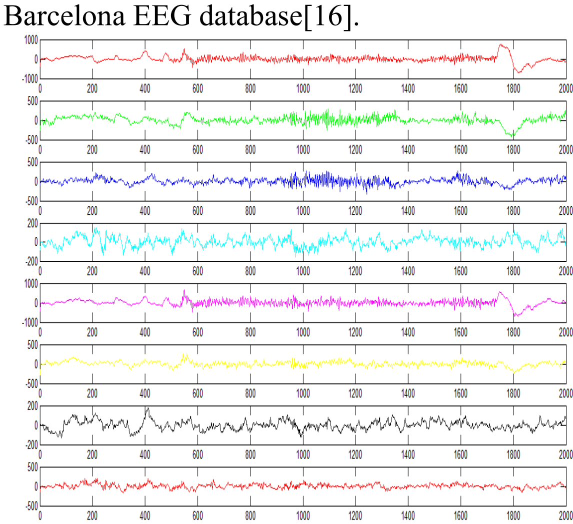

Figure 2. EEG samples collected from healthy persons without any epileptic disorder.

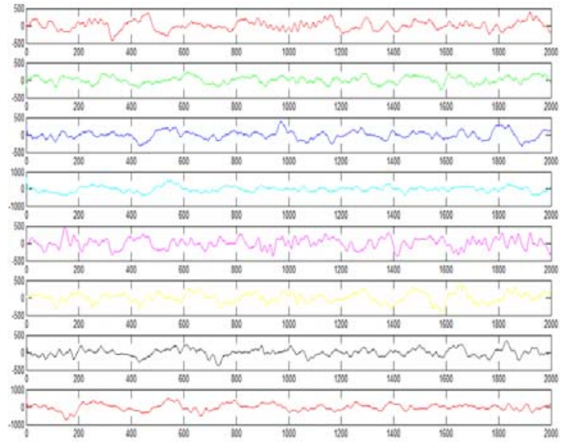

Figure 3. EEG samples collected from the persons having epileptic disorder.

The Schematic Block Overview of the proposed epileptic seizure classification system is shown in Fig. 4. The proposed approach initially performs the data acquisition process to obtain the EEG datasets for both training and testing. The acquired EEG datasets are first preprocessed to remove the noise if any and to enhance it further. A detailed time-frequency analysis is carried out on the denoised EEG datasets to identify the characteristic fragments in the EEG waveforms. An algebraic interpolation and a detailed statistical analysis are carried out on the fragmented EEG datasets to extract the characteristic and symptomatic features like approximate entropies, sample entropies, wavelet coefficient and sub-energies. Later, the extracted features are subjected to model statistically by aptly amalgamating all these positive features of healthy neural activities to compute a threshold vector which acts as a border of classification between the epileptic and non-epileptic features. Finally, all these extracted threshold features are applied as training and testing sets to a pattern classification based Artificial Neural Network (ANN), K-Nearest Neighbors (KNN) and a support vector machine and a parametric performance comparison is done between them.

While extracting the features from EEG waveforms, each EEG waveform is analyzed into five segments such as A, B, C, D, E and a totally 65 features are extracted from both training and testing sets. A brief description of these features is given (see Table I).

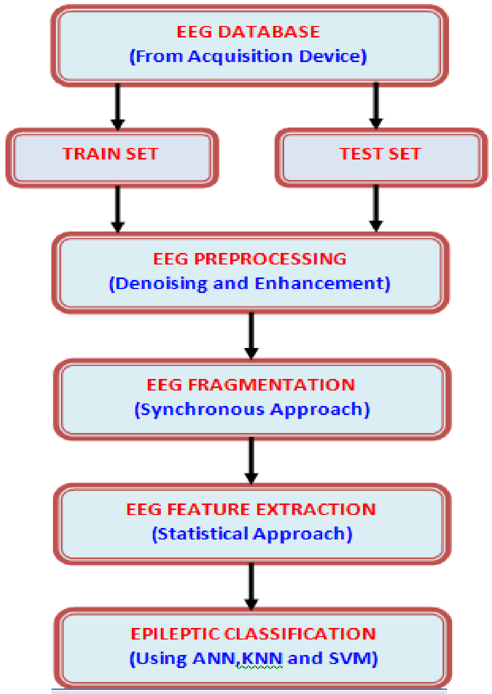

Figure 4. Schematic block overview of the proposed Seizure Classification approach.

A. Classification Using ANN:

Artificial Neural Networks are a family of statistical learning models in Machine learning and Cognitive science, inspired by biological neural networks. Now for Epileptic seizure Classification using ANN, the ANN is trained with training dataset using machine learning process and the performance is tested with the test EEG dataset.

B. Classification Using KNN:

KNN is a kind of instance learning algorithm, in which the function is approximated locally only and all calculation differs until the classification. The KNN algorithm is one of the simplest Machine Learning algorithms. Classification with an instant classifier can be a straightforward task of locating the nearest neighbor in instance set and cataloging the unknown instance with the same class label as that of the located (known) neighbor. In KNN classification, the output is a class membership. The training and testing datasets of epileptic EEG classification are applied to KNN to perform classification and the classification results are documented.

C. Classification Using SVM:

The Support Vector Machine is a new Machine learning approach used for binary classification. Epileptic classification of EEG signals can be done by feeding the EEG features to Support Vector Machines (SVM).

In classification using SVM, epilepsy detection adopted the state of the art Support Vector Machine (SVM) method, which is predominantly effective in numerous application fields including the epileptic classification of EEG signals. A set of known features are called the training data. Based on the training data, the learning algorithm extracts a decision function to classify the unknown input data called test set. SVM continuously minimizes the empirical classification error and maximizes the geometric margin, so SVM also called Maximum margin classifier.

For an EEG signal its approximate and sample entropies are computed using the mathematical analysis presented as follows. For a given EEG signal of length 'k',a set of 'k' dimensional vectors Y_i^k,can be formulated from a scalar time series Y_i;i=0,1,2,…..N-1 such that $Y_i^k = [y_{i-(m-1)}, y_{i-(m-1)+1}, y_{i-(m-1)+2}, \cdots, y_i]$.In addition a set of k+1 dimensional vectors Y_i^{k+1} can be obtained accordingly. For the ith k and km+1 dimensional vectors, the number of their neighborhood points within δ can be counted and normalized to the total number of vectors.

$$C_i^k = \frac{1}{N-(k-1)} \sum_{|i-j| \le \varepsilon} H(|y_i^k - y_j^k| - \delta)$$

And

$$C_i^{k+1} = \frac{1}{N-m} \sum_{|i-j| \le \varepsilon} H(|y_i^{k+1} - y_j^{k+1}| - \delta)$$

Now the approximate entropy [15] can be calculated as

$$AE(k,\delta,N) = \frac{1}{N\ \ (k\ \ 1)} \sum_i \log(C_i^k) - \frac{1}{N\ \ k} \sum_i \log(C_i^{k+1})$$

Where H is the Heaviside function and $|y_i^k - y_j^k|$ is a measure of the distance between the vectors y_i^k and y_j^k.The Distance threshold δ is usually chosen based on the standard deviation of time-series Y_i.Next, the input EEG signal is transformed to its spectral domain by a separable Discrete Wavelet Transform (DWT) to obtain the vital features based on sub-band coefficient energies. The analysis stage of the DWT implements a pair of low pass ($H_0(n)$) and high pass ($H_1(n)$) filters to decompose the signal into spectral domain, whereas the synthesis stage implements another reversible pair of low pass ($G_0(n)$) and high pass($G_1(n)$) filters to revert the signal from spectral domain to time domain as shown in fig(5)

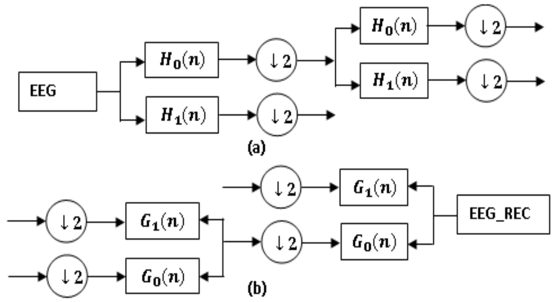

Figure 5. Discrete Wavelet Transform trees ;(a) for Analysis,(b) for synthesis.

TABLE I

EEG FEATURES USED FOR EPILEPTIC SEIZURE CLASSIFICATION.

Parameter	Features				
Minimum	1)A_{min}	2)B_{min}	3)C_{min}	4)D_{min}	5)E_{min}
Maximum	6)A_{max}	7)B_{max}	8)C_{max}	9)D_{max}	10)E_{max}
Average	11)A_{avg}	12)B_{avg}	13)C_{avg}	14)D_{avg}	15)E_{avg}
Median	16)A_{med}	17)B_{med}	18)C_{med}	19)D_{med}	20)E_{med}
Standard Deviation	21)A_{std}	22) B_{std}	23) C_{std}	24) D_{std}	25) E_{std}
Variance	26)A_{var}	27) B_{var}	28) C_{var}	29) D_{var}	30) E_{var}
Range	31)A_{rang}	32)B_{rang}	33)C_{rang}	34)D_{rang}	35)E_{rang}
Approximate entropy	36)A_{apen}	37)B_{apen}	38)C_{apen}	39)D_{apen}	40)E_{apen}
Entropy	41)A_{en}	42) B_{en}	43) C_{en}	44) D_{en}	45) E_{en}
Geometric Mean	46)A_{gm}	47) B_{gm}	48) C_{gm}	49) D_{gm}	50) E_{gm}
Sample Entropy	51)A_{sen}	52) B_{sen}	53) C_{sen}	54) D_{sen}	55) E_{sen}
Skew	56)A_{skew}	57)B_{skew}	58)C_{skew}	59)D_{skew}	60)E_{skew}
Kurtosis	61)A_{kur}	62) B_{kur}	63) C_{kur}	64) D_{kur}	65) E_{kur}

IV. RESULTS AND DISCUSSION

In this paper we proposed, designed, developed and implemented an efficient approach for thresholding and classification of the epileptic and non-epileptic seizures with the aid of statistical features. The proposed epileptic seizure classification algorithms are implemented and simulated in the Matlab environment and the simulation results are presented in this section. Simulation results of an epileptic seizure classification algorithm with ANN are presented as follows.

According to the confusion matrix obtained, it is observed that, the classification algorithm using ANN achieves a True Positive Rate (TPR) of 95%, overall accuracy of 95%, overall sensitivity of 94.4286%, overall specificity of 94.4286%, overall precision of 95.3221% and overall feature matching score of 94.8093.

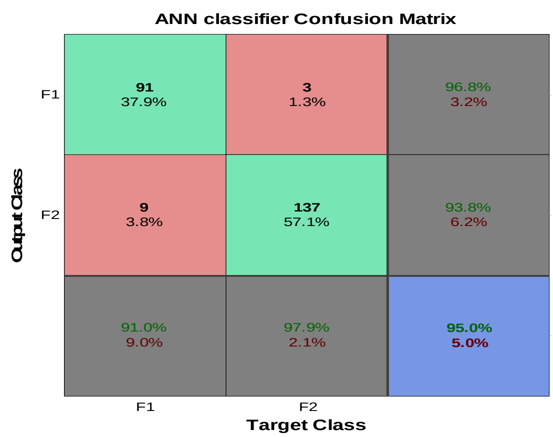

Figure 6. Confusion matrix of Epileptic Seizure Classification using ANN

Finally the simulation results of an SVM based epileptic seizure classification algorithm are illustrated in Fig. 8. From the confusion matrix of SVM based epileptic seizure classification algorithm, it is observed that SVM approach achieves all time high classification performance compared to ANN and KNN. It achieves an overall TPR of 95.8333%, overall accuracy of 95.8333%, overall sensitivity of 95.7143%, overall specificity of 95.7143%, overall precision of 95.7143% and overall feature matching score of 95.7143%.Classification performances of all the three epileptic seizure classification algorithms are summarized (see Table II).

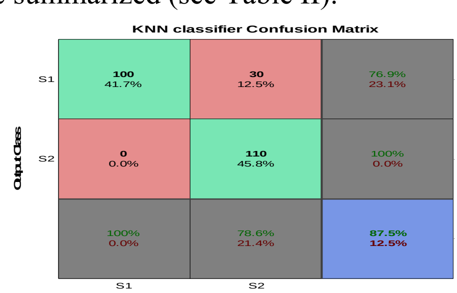

Figure 7. Confusion matrix of Epileptic Classification using KNN.

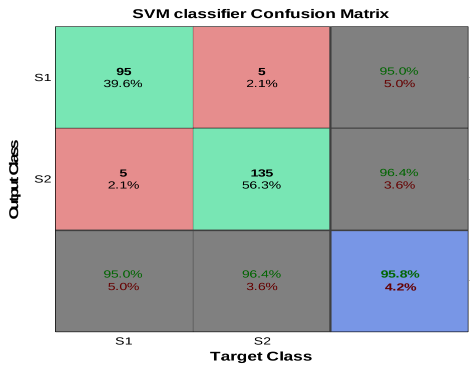

Figure 8. Confusion matrix of Epileptic Classification using SVM

TABLE II
PERFORMANCE SUMMARY OF AN EPILEPTIC SEIZURE CLASSIFICATION

S NO	Parameter	ANN	KNN	SVM
1	TPR	95.00	87.5	95.8333
2	ACCURACY	95.00	87.5	95.8333
3	SENSITIVITY	94.4286	89.2857	95.7143
4	SPECIFICITY	94.4286	89.2857	95.7143
5	PRECISION	95.3221	88.4615	95.7143
6	F SCORE	94.8093	87.4783	95.7143

From the comparison, it is observed that SVM classifier based epileptic seizure classification algorithm show predominantly better classification accuracy over the classification algorithms based on ANN and KNN. All the performance parameters of SVM shown better results compared to ANN and KNN.

V. CONCLUSION

In this paper, an efficient approach for thresholding and classification of the epileptic and non-epileptic seizures with the aid of statistical features is adopted. The proposed approach initially performs an algebraic interpolation of various normal seizure signals of numerous healthy collections to extract the characteristic, statistical and symptomatic features. An effective feature extraction method for EEG is developed which extracts five synchronous fragments from both training and testing sets and totally 65 features are calculated. Performance of the proposed epileptic seizure classification system is verified with different Machine Learning algorithms like ANN, KNN, and SVM. A comparative analysis for Performance parameters are made with different classifiers which shows SVM classifier provides 95.8333 % overall classification accuracy.

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