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Detection of Epileptic Seizure in EEG Recordings by Spectral Method and Statistical Analysis

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Abstract: Electroencephalographs are records of brain electrical activity. It is an indispensable tool for diagnosing epileptic seizure. Manually reviewing EEG recordings for detection of epilepsy pattern is a time-consuming process. It is, therefore, necessary to automate the epileptic seizure detection. Further analyzing after the detection using large data set is a good supplement to the wide range of algorithms currently used for analysis. Seizure evolution is typically a dynamic and non stationary process and the EEG signals are composed of many frequency bands. The objective of this work was to determine features that differentiated epileptic seizure from a normal activity. Subjects suffering from a commonly occurring generalized epileptic seizure EEG segments and non seizure EEG segments are used for the study. The Spectral and Statistical methods are applied to the signal and the features are extracted. Spectral power, Standard deviation, Variance, Root Mean Square and Measure of Spread are the features that differentiate abnormal activity from normal activity whereas Median, Mode, Skewness, kurtosis are not able to differentiate. This study gives a method to detection of seizure and analysis in offline. It can be further extended to the real time. The algorithm is tested with two different databases covering children and as well as adult data sets.

Key words: Electroencephalograph, epileptic seizure, time series signal, fast Fourier transform, power spectrum, statistical analysis

INTRODUCTION

Epilepsy is a common chronic neurological disorder, affecting almost 50 million people worldwide (WHO, 2007). Epileptic seizures are paroxysmal brain dysfunction caused by excessive neuronal discharge (Fix, 1995). It is associated with some altered state of consciousness, recurrent and sudden malfunction of the brain. EEG used to be a first-line diagnosis test. The diagnosis of epilepsy also achieved by different examinations, such as Positron Emission Tomography, Magnetic Resonance Imaging, Computed Tomography and Electroencephalogram (EEG). Of these, EEG most is important and economical one which gives high temporal resolution. A lot of useful information in EEG can be extracted by signal processing methods (Gevins *et al.*, 1995, Mansouri *et al.*, 2012). Some of the information is helpful for diagnosis and treatment of epilepsy patients (Wang and Xu, 2009). The research work on epileptic EEG processing mainly focuses on epileptic events detection and seizure prediction. In the epileptic EEG, the presence of epileptiform activities, such as spikes, slow rhythm and high-frequency epileptiform oscillations confirms the diagnosis of epilepsy (Padmasai *et al.*, 2010). Traditionally, EEGs are scanned for epileptic spikes by experienced physicians. With the development of EEG acquisition system, long-term EEG collection can be achieved.

Approximately, 1% of the world's population is affected by epilepsy and 25% of epilepsy patients cannot be treated sufficiently by any available therapy 80 people per day develops the condition (WHO, 2007; Liang *et al.*, 2010). Quality of life of a person may be severely affected by epilepsy because of both psychological and social reasons. If an automatic seizure-detection system is available, it could reduce the time required by a neurologist to perform an off-line diagnosis by reviewing

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electroencephalogram data. It could be used to produce an on-line warning signal to alert healthcare professionals (Liang *et al*., 2010). Seizure evolution is typically a dynamic and non stationary process and the signals are composed of multiple frequencies. Visual and conventional frequency-based direct spectral method has limited application (Tzallas *et al*., 2009). An algorithm proposed applying wavelet packet analysis and determined dominant frequency bands during electro convulsive therapy (Zandi *et al*., 2007). Wavelet analysis method to isolate EEG bands had shown good performance (Tafreshi *et al* 2006). A method proposed based on the standard clinical sub bands of EEG (Yucel and Ozguler, 2008).A simplified method of feature extraction and classification proposed by the method based on energy ,entropy and kurtosis were considered for discrimination of various categories of EEG signals (Pal and Panda, 2010). The statistical method combined with a simplified classification algorithm was proposed to discriminate epileptic EEG signal (Choe *et al*., 2010).

The main objective of the present proposed work is to detect the seizures in EEG signal and extracting the features for further analysis. The proposed method uses an algorithm based on combined spectral and statistical methods. The combined analysis of identified features from various age group and large dataset could reveal better results. This work is to automate the detection process and to help the doctors in analyzing the seizure EEG signal.

MATERIALS AND METHODS

We worked with the database collected from (Andrzejak *et al*., 2001) the Epilepsy Centre at the University of Bonn, Germany (http://epileptologie-bonn.de). In this study, two sets of EEG, B and E, each containing (normal and seizure signal) 100 single channel EEG segments of 23.6 seconds duration with a sampling rate of 173 Hz, are considered. The spectral bandwidth of the data set from 0.5 Hz to 85 Hz is used for detection and analysis. EEG time series data made available online by the Children's Hospital Boston, consisting of EEG recording of subjects with intractable seizures are also considered (http://physionet.org/physiobank/database/chbmit/). Data sets available are filtered already using hardware filters 0.5-70 Hz and 50 Hz notch filters. Recordings are from 22 subjects (5 males, ages 3-22 and 17 females, ages 1.5-18). Mean (Standard Deviation) ages of the patients are 9.81 (5.75 years). The International 10-20 system of EEG electrode positions and nomenclature are used for 23 channels. These recordings are FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8 and T8-P8. All signals are sampled at 256 samples per second with 16-bit resolution and EEG data recorded is exactly one hour of digitized signal duration, some are of two hour duration and some other 4 h duration. From this set, 50 segments of normal EEG are considered as non seizure conditions and 50 segments of EEG with seizure are considered as seizure cases for the present work. The conditions namely non seizure and seizure and the duration are specified in the database itself.

The data used in this investigation have been collected from two databases as mentioned above. The EEG from Epilepsy Centre at the University of Bonn, Germany (http://epileptologie-bonn.de) is used for finding spectral, statistical features and to classify normal and seizure. For the purpose of EEG time series seizure detection and analysis, the second data set from the database of Children's Hospital Boston is used (http://physionet.org/physiobank). To present the results, the algorithm is tested using single channel (C_z-P_z) 50 normal and 50 seizure EEG time series segments. The seizure cases known as generalized as given in database are used as gold standard (Andrzejak *et al*., 2001), (http://physionet.org/physiobank/database/chbmit/). Figure 1 shows the block diagram of the model for a proposed method.

Pre processing: The EEG data are containing many artifacts, such as power line noise and movement. The recordings of single channel EEG segments collected from the databases (Andrzejak *et al*., 2001 and http://epileptologie-bonn.de and Children's Hospital Boston) are first taken into the Lab VIEW platform and EEG signal baseline wanders is corrected and the signal amplitude is quantified to micro volts. The EEG signal is filtered using a digital low pass Finite Impulse Response (FIR) filter with Hamming window technique to remove power line noise along with out-of band noise. The order of the filter is 40 and cut off frequency is 32 Hz. Flatness without a ripple in the pass band is desirable in the analysis of EEG signals which leads to the use of FIR filter (Lessard, 2006). Filtered EEG segments are chosen for seizure detection and analysis. A normal EEG and seizure EEG segments are shown in Fig. 3a and 4a.

Outline of spectral method: EEG is a non stationary signal and hence applying linear methods to compute direct spectrum results in less resolution (Blanco *et al*., 1998). For the preprocessed normal and seizure EEG segments,

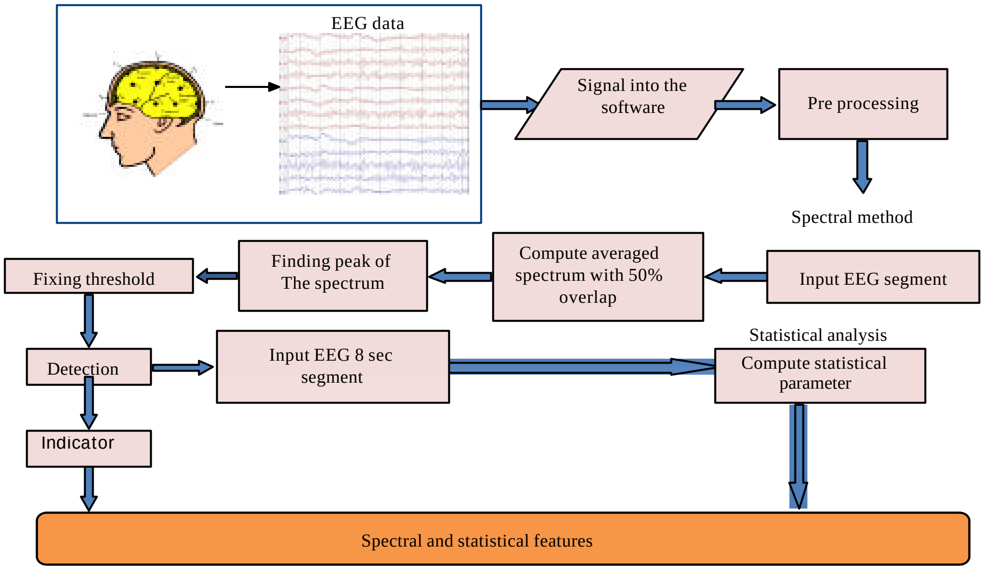

Fig. 1: Schematic drawing of the proposed method

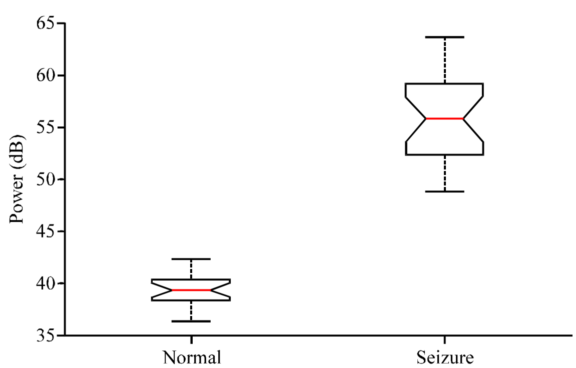

Fig. 2: Box plot for 25 non seizure and 25 seizure segments

averaged spectrum and averaged power measure are calculated by the following procedure. Spectral analysis is estimation of power from the observation of the signal over time. The Power spectrum of the signal is computed using Fast Fourier Transform (FFT) for every two-second window with an overlap of one second of the signal (Djuric and Kay, 1999; Rangayyan, 2002). The equation for FFT is given in Eq. 1. The computation of Fourier transform by definition:

$$X(k) = \sum_{k=1}^{N-1} x(n) W_N^{kn} : \quad k = 0, \ldots, N-1 \tag{1}$$

We know that:

$$W_N = e^{-j\frac{2\pi}{N}}$$

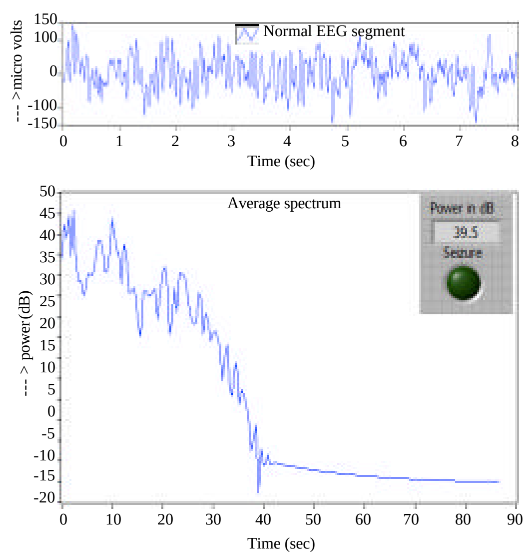

Fig. 3(a-b): Normal EEG segment and its averaged spectrum, LED is in 'OFF' condition (a) Normal EEG segment and (b) Average spectrum

For one value of 'k' observe that the multiplication of x(n) and W_N^{kn} is done for 'N' times, since n = 0 to N-1. That is there are 'N' complex multiplications for one value of k. Since, 'K' also has 'N' values (since k = 0, 1, ..., N-1).

RESULTS

Spectral based detection: Consider sequence $\{x[n]\}_0^{N-1}$, that is x(n) ,n = 0, 1,..., N-1. To find the periodogram of

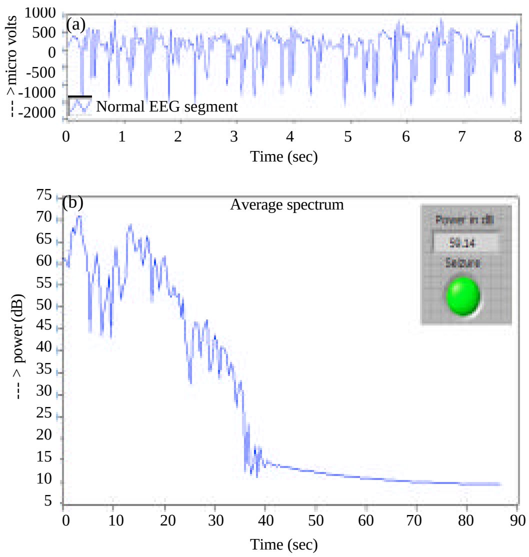

Fig. 4(a-b): Seizure EEG segment and its averaged power spectrum, LED is in 'ON' condition (a) Seizure EGG segment and (b) Averaged spectrum

data x[n],we split up the N-point data record into M-point segments $x_i[n]$ that overlap with each other by segments of length L, such that ith segment is given by the sequence $x_i[n]$. The sequence $\{x_i[n]\}^{L-1}_{0}$, that overlaps successive sequences by D samples. Then = L+D (K-1), here N is the total number of samples in the entire EEG time series data, L is the length of the segment and D is the overlapping samples. The *l*th sequence is denoted by:

$$\begin{gathered} x_t[n]-x[n+(i-k)D] \\ n = 0, 1,..., L-1 \\ i = 1, 2...K \end{gathered} \tag{2}$$

where, x_i [n] is the signal to be analysed and [n] the weighting or temporal window of null value outside the observation interval. This temporal product is transformed into the frequency domain by a convolution product of the Fourier transforms of the sequence and window. The Hamming window technique offers a very simple means of (linear) Zero phases, stable, simpler and easier for our application (Sadati *et al*., 2006). EEG signals are transformed from a time domain to a frequency domain. Here, we used Welch Overlapping Averaged Spectral (WOSA) method. The averaged spectrum is calculated using Hamming window considering 50% overlap. The averaged power is thus computed by using Welch Overlapped Spectral Averaging (WOSA) method. Hamming window function is used in the averaging process covering from delta (δ) to alpha (α).

Table 1: Spectral power computed for 25 normal and 25 seizure segments.

	Normal (power in dB)	Seizure (power in dB)
Mean	39.45	55.80
SD	2.15	4.37

SD: Standard deviation

The spectral power of the *i*th segment is:

$$X^{(i)}_{avg}(f) = \frac{1}{L}\left|\sum_{n=0}^{L-1} W[n]\, x_i\, [n] e^{-j2fn}\right|^2 \tag{3}$$

Here, $X^{(i)}_{avg}(f)$ is the averaged periodogram of the data samples x[n] weighted by a Hamming window w[n].The spectrum obtained is given by:

$$P_M(f) = \frac{1}{K}\sum_{i=1}^{K} X^{(i)}_{avg} \tag{4}$$

where, M = 0, 1, 2 ...K segments. Now spectral power is computed using relation:

$$P_{M(eeg\ band)}(f) = \frac{1}{f2-f1}\sum_{f=f1=0.5}^{f2=14} P_M(f) \tag{5}$$

Here, $X^{(i)}_{avg}(f)$ is the averaged periodogram of the data sample x[n] weighted by hamming window. The frequency band from 0.5 Hz to 14 Hz is considered for further processing as this band covers δ, θ and α. The seizure activity has generally been considered to be associated with these bands. The researchers also point out that frequency dynamics characterized by an activity of seizure are originally at alpha and are slowing down to about delta (Zandi *et al*., 2007; Tafreshi *et al*., 2006). From the averaged spectrum, the average power for the frequency range from 0.5 Hz to 14 Hz is thus calculated. This power value is shown in the upper right corner in Fig. 3b. This value of average power will be helpful in finding the presence of seizure. The average power value is computed for each 8 second segments of EEG data. This is performed for 25 normal EEG segments and 25 EEG segments with seizure condition. The average power value for the 25 segments found out to be 39.45 dB with Standard Deviation (SD) of 2.15 and the same for seizure condition is 55.80 dB with SD of 4.37. These two values show a large difference in average power value and during seizure, the value is much higher than normal. This concept is applied further to detect epileptic seizure from EEG. The seizure is detected by looking for elevation of power during the seizure compared to normal. The average spectral powers for the 25 normal and 25 seizure segments (Andrzejak *et al*., 2001) are tabulated in Table 1. The results are presented graphically using box plot as shown in Fig. 2. The averaged power spectral value of 25 normal and 25 epileptic EEG signals are analyzed to fix the threshold value (Zandi *et al*., 2007; Rangayyan, 2002). The threshold value is fixed as 48 dB for detecting the seizure based on the non overlap region in the box plot. If there is a seizure, the elevation of power in the spectrum is more.

Totally, the database has 100 segments each for normal and seizure conditions. Out of these 25 cases from each are analyzed for spectral variations. For the remaining 75 segments of EEG of each normal and seizure data, the average power value is calculated for the 0.5-14 Hz range as before and when the average power in the 8 second segment is less than the threshold of 48 dB, a green LED in the upper right corner of panel is shown in the off condition and the plot of average power spectrum is shown (Fig. 3b). When the average power is greater than 48 dB, it is detected as seizure in the 8 second segment and the LED will be made on (Fig. 4b). The average spectral powers for the remaining 75 normal and 75 seizure segments are calculated for data set segments (Andrzejak *et al*., 2001).

Spectral method for children hospital EEG time series data set: We also extended our work with EEG time-series data collected from the children's hospital Boston. We only used single channel (CZ-PZ) data for development and testing of the seizure detection algorithm (Greene *et al*., 2008; Hoeve *et al*., 2001). Non seizure EEG time series signal of a subject as shown in Fig. 5a and a seizure signal of another subject is shown in Fig. 6a. EEG signals are transformed from a time domain to a frequency domain.

The selected peak points are shown in Fig. 5c and Fig. 6c for normal and seizure conditions, respectively. This peak point is mapped to the time series EEG and this point as the centre point, a window has to be chosen (Fig. 5d, 6d). Here, we used Welch Overlapping Averaged Spectral (WOSA) method. The averaged spectrum is calculated using Hamming window considering two seconds segments with an overlap of one second. The relative spectral power is computed from the Eq. 3. The relative spectral power peak value is detected (Fig. 5b, 6b). According to the researchers, the minimum seizure duration is 10 seconds (Zandi *et al*., 2007; Bruce, 2006). Taking this into consideration a window of 8 second data are selected for detection and analysis (Fig. 5e, 6e). Figure 5f and 6f show the detected results by the algorithm and this well coincides with the diagnosis results given by the doctor in the database.

This box plot shows that there is a clear demarcation in the spectral power values during seizure and normal EEG and the value considered for this work is as follows; if power less than 48 dB no seizure. If power is greater than 48 dB, seizure condition.

To show the performance of the method for full data set 150 seizure EEG and 150 non seizure EEG segments the result obtained are tabulated in the Table 2 .The spectral analysis results are plotted graphically in the Fig. 7.

Table 2: Spectral powers computed for 150 non seizure and 150 seizure segments

	Normal (power in dB)	Seizure (power in dB)
Mean	40.67	54.61
SD	2.44	6.73

SD: Standard deviation

Table 3: Detection results

	Positive (+)	Negative (-)
Seizure (+)	(TP) 140	(FN) 10
Non seizure (-)	(FP) 4	(TN) 146

TP: True positive, FN: False negative, FP: False positive, TN: True negative

Sensitivity, specificity and accuracy measures: The EEG segments are executed for detecting seizure. Table 3 shows the test result of the spectral method.

The sensitivity (S_n) of seizure detection is the probability that the detection is positive when the EEG segments are with the seizure. The specificity (S_p) is defined as the probability that the seizure detection result says a non seizure segment, when in fact, they are seizure free:

$$\text{Sensitivity } (S_n) = \frac{TP}{(TP + FN)} \times 100 \tag{6}$$

$$\text{Specificity } (S_p) = \frac{TP}{(TP + FN)} \times 100 \tag{7}$$

$$\text{Accuracy} = \frac{TP + TN}{(TN + FP + TN + FN)} \times 100 \tag{8}$$

The three measures sensitivity, specificity and accuracy are used as evaluation criteria to check the performance of the proposed detection method. The result of detection method is shown in Table 3.

There are 150 normal EEG segments and 150 seizure EEG segments for the both databases put together. The sensitivity of the proposed algorithm is 93% specificity is 97% and overall accuracy is 95%.

Statistical analysis: Statistical methods provide information on the amplitude variation of EEG signal. Statistical parameters used are Mean, Mode, Variance, Standard Deviation, Measure of Spread, Skewness, kurtosis and RMS of EEG for understanding normal and seizure features. The unit of amplitude variation of EEG signal is in micro volts. The mean, standard deviation, RMS and Measure of Spread have the same units as the

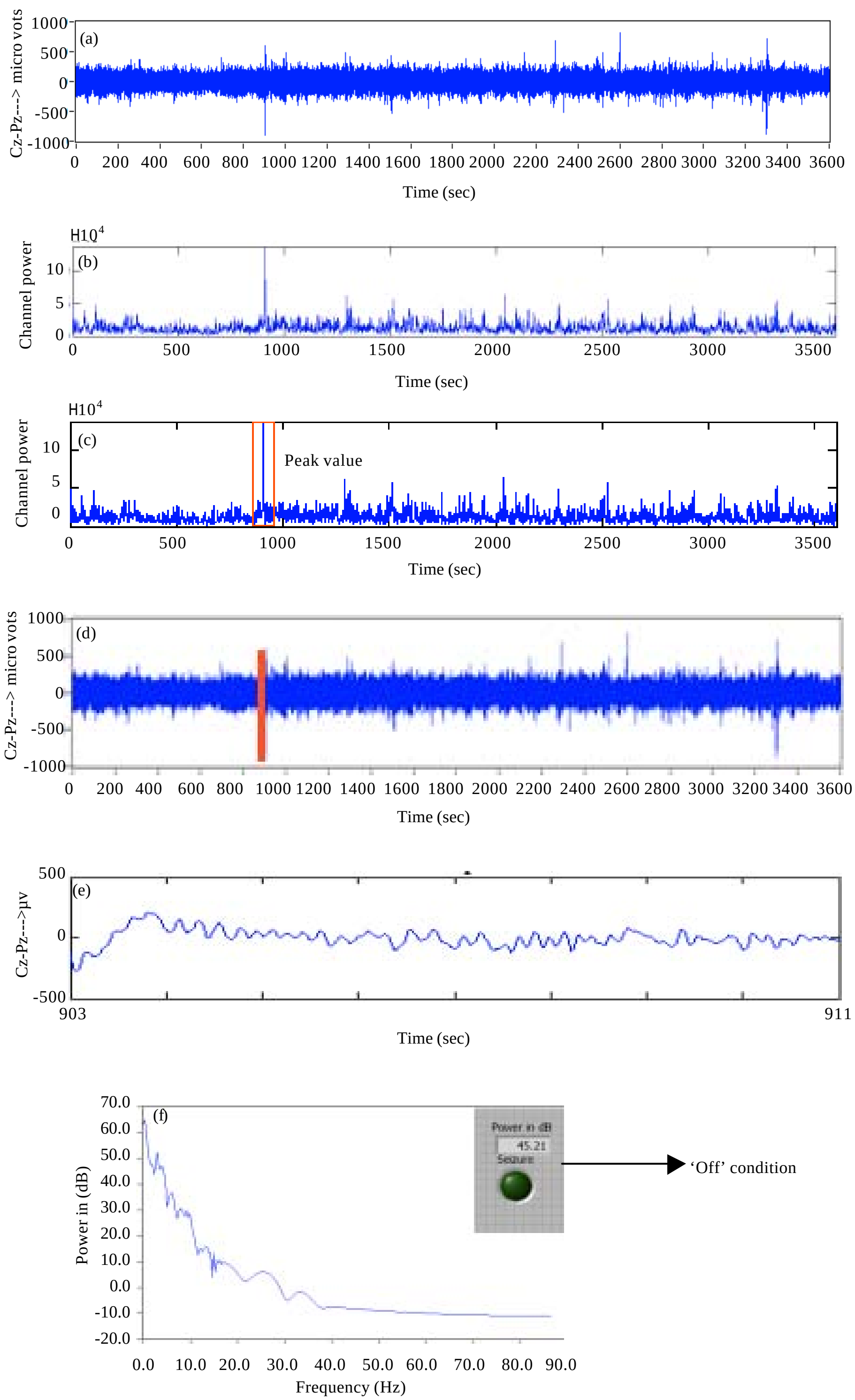

Fig. 5: Normal time series and its spectral power, LED is in 'OFF' condition (a) EEG normal time series, (b) Relative power in egg segment, (d) EEG normal time series, (e) 8 sec epoch and (f) Averaged spectrum

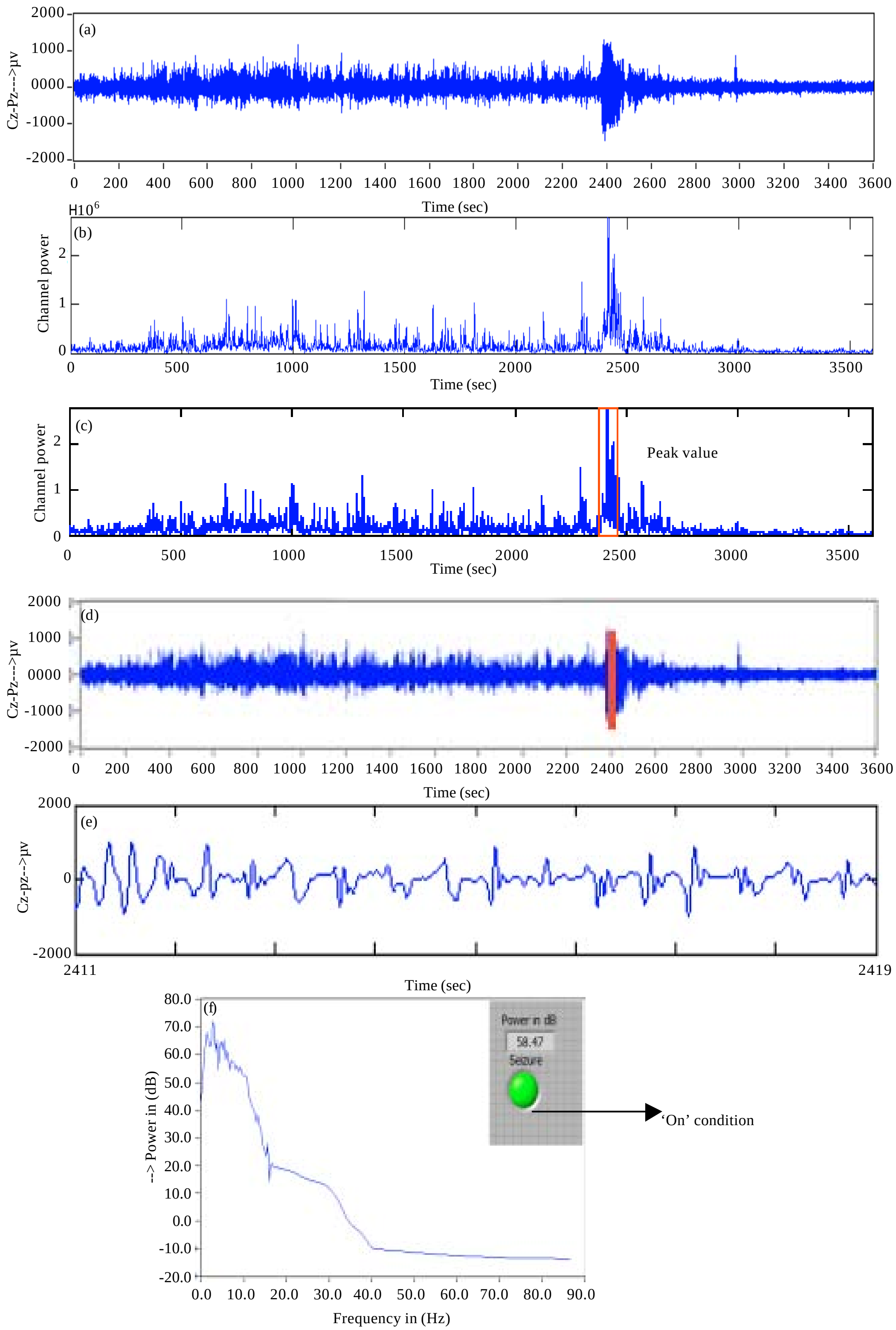

Fig. 6: Seizure time series and its Spectral power, LED is in 'ON' condition (a) EEG normal time series, (b) Relative power in egg segment, (d) EEG normal time series, (e) 8 sec epoch and (f) Averaged spectrum

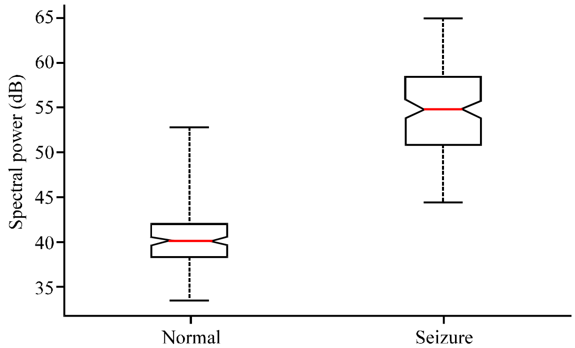

Fig. 7: Box plot for 150 non seizure and 150 seizure segments

EEG signal amplitude which is in micro volts whereas unit of variance is the square of the micro volts. Skewness and kurtosis have no units; it is a pure number like a Z-score.

The Arithmetic Mean is the standard average, often simply called the mean. For a given EEG signal, the mean value of the EEG data at any point in time, n is the average value of its sample functions at a fixed time (Bruce, 2006). The Mean of the signal is calculated by using the Equation:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{9}$$

The Mode is the value that occurs most frequently in a data set or a probability distribution. The variance is the mean of the squared differences between individual data points and the mean of the array. Variance is calculated by using the Eq. 10:

$$v = \sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \tag{10}$$

The standard deviation is the square root of the variance. A Measure of Spread tells us a whether data sample is spread out or scattered. We can use the range to measure the spread of a sample. We get a good measure of spread by summing the squares of the deviations from the mean. The Root Mean square (abbreviated RMS), also known as the quadratic mean, is a statistical measure of the magnitude of a varying quantity. RMS is calculated by Eq. 11:

$$\bar{x}_{rms} = \sqrt{\frac{x_1^2 + x_2^2 + x_3^2 + \ldots x_N^2}{N}} \tag{11}$$

Range is used to explain the variability in an EEG segment samples. It is used in connection with a measure of central tendency, such as the mean, median, to provide overall description of a set of EEG samples that is Measure of Spread MOS. Quartiles tell us about the measure of spread. The quartiles are computed by breaking data set into quarters. The measures available in quartiles are first quartile (Q1), second quartile (Q2) and third quartile (Q3). A common measure of expressing a quartile is an inter quarter range (Q3-Q1). Hence, for EEG data segment the inter quartile range is:

$$\text{Inter quartile range} = \text{IQR} = \text{Q3-Q1} \tag{12}$$

Skewness describes asymmetry from the normal distribution in a set of statistical data, as data becomes more symmetrical as its value approaches zero. Normally distributed data, by definition has little skewness and on other hand positively skewed or right sided skewed data has positive and negatively skewed or left sided skewed has negative value. Skewness can be calculated by the Eq. 13:

$$\text{Skewness} = \frac{\Sigma\left(\frac{x - \bar{x}}{\sigma}\right)^3}{n} \tag{13}$$

Kurtosis is a statistical measure used to describe the distribution of observed data around the mean. It is the degree to which a data set is peaked. Kurtosis can be calculated mathematically by the Eq. 14:

$$\text{Kurtosis} = \frac{\Sigma\left(\frac{x - \bar{x}}{\sigma}\right)^3}{n} - 3 \tag{14}$$

These statistical values are computed for already detected normal and seizure segments of 8 second duration each. The results obtained for variance, root mean square, standard deviation, measure of spread and inter quartile range for the normal and seizure EEG signals are plotted in the Fig. 8.

In the analysis, all parameters are computed based on the equations given above. The statistical parameters for the 150 normal and 150 seizure segments (Andrzejak *et al*., 2001 and Epilepsy Centre at the University of Bonn, Germany http://epileptologie-bonn.de) obtained are tabulated in Table 4. The box plot in Fig. 9 shows a distribution of statistical features computed for 150 normal and 150 seizure segments. From the figures it can be clearly seen that wide difference is there in all parameters for normal and seizure conditions.

The algorithm is tested on a test data (http://www.vis.caltech.edu/~rodri/data.htm). The spectral method is applied on test data and the instant at which seizure occurs are identified (power spectral value of 51 dB). This correlates with the gold standard for member.

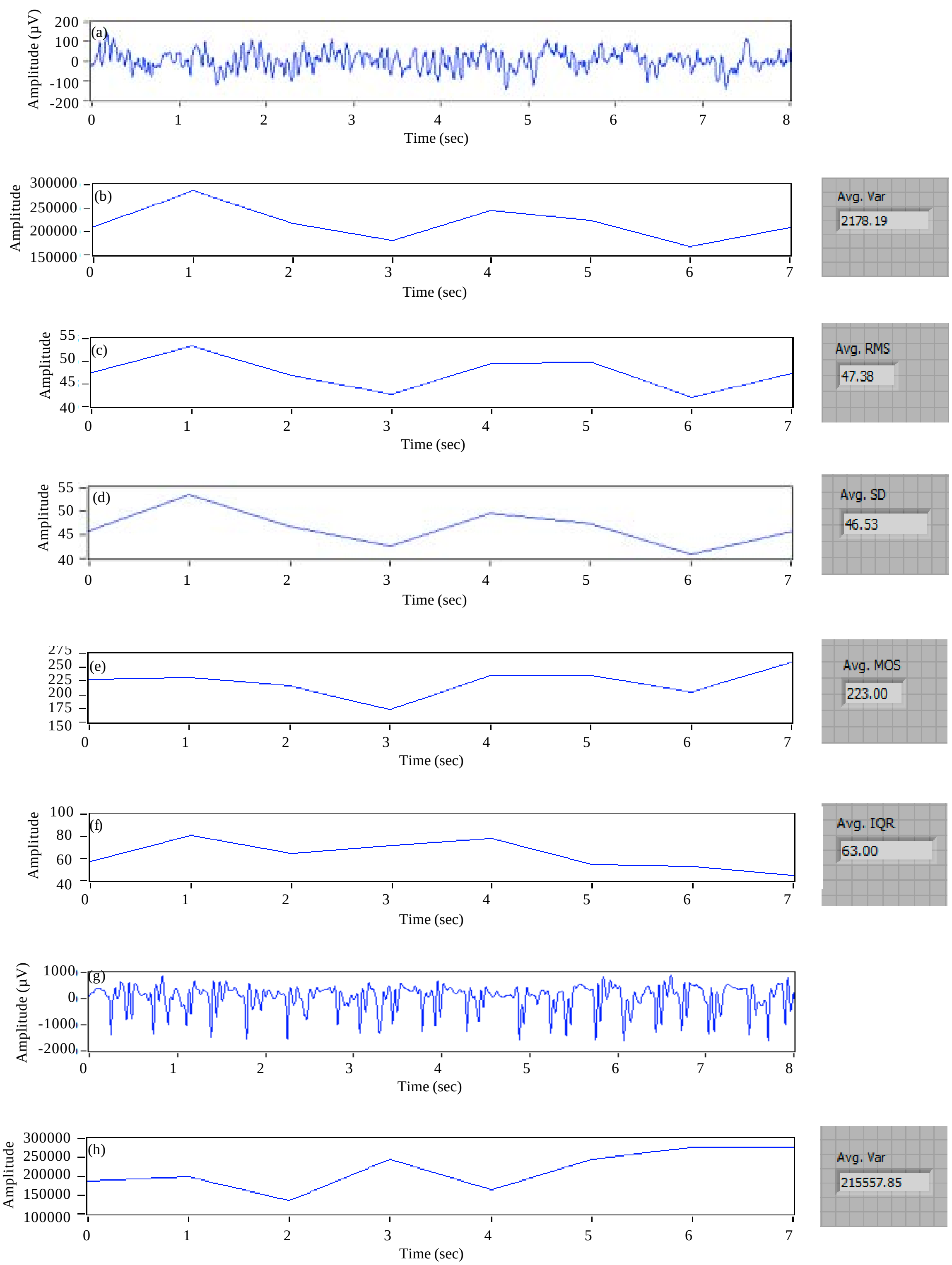

Fig. 8(a-l): Continue

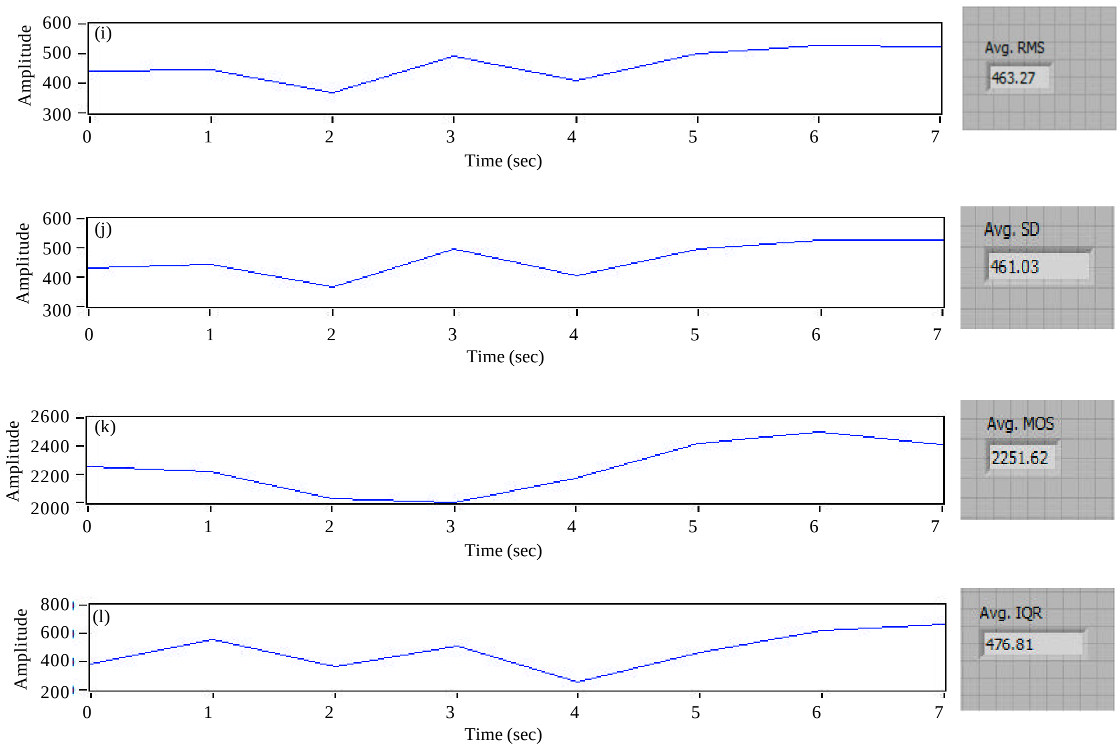

Fig. 8(a-l): Statistical parameters for normal and seizure segment (a) Normal EEG segment, (b) Variance, (c) RMS, (d) SD, (e) MOS, (f) IQR, (g) Seizure EEG segment, (h) Variance, (i) RMS, (j) SD, (k) MOS and (l) IQR

Table 4: Statistical parameters computed for 150 normal and 150 seizure segments

	Variance	RMS	SD	MOS	IQR	Skewness	Kurtosis
Normal							
Mean	3404	59.97	55.73	317.68	70.66	-0.01	3.08
Seizure							
Mean	90177	255.38	258.86	1467.17	326.38	0.04	3.08

RMS: Root mean square, SD: Standard deviation, MOS: Measure of spread and IQR: Inter quartile range

The statistical parameters for the seizure durations are computed and they fall in the ranges specified for seizure condition (variance of 26963, RMS of 163.24, SD of 163.59 and MOS of 733.50 and Range of 218.82). This shows the efficiency of the algorithm in detecting the seizure.

Here Variance, Standard deviation, RMS and Measure of spread shows some good variation during seizure period. Other parameters like Mean, Mode, Skewness and kurtosis do not show much variation in the seizure period. So the parameters variances, Standard deviation, RMS, MOS are considered for analysis.

RESULTS AND DISCUSSION

In this study, a method to detect epileptic seizure in an automatic manner is proposed. Power in the EEG signal is relatively increased during the seizure. Taking this into consideration, first method uses the spectral technique for detection and analysis. For this, EEG signal from (Andrzejak *et al*., 2001) 100 normal and 100 segments with epileptic seizure are tested and analyzed. All 100 normal cases are identified correctly but 95 out of 100 epileptic seizure conditions are detected correctly by the algorithm. The results clearly show that functional differences during normal and seizure activities. . The discussion of our study in comparison to researches that deal with detection of epileptic seizure from EEG recordings of same database (Andrzejak *et al*., 2001) is given in Table 5. The result obtained using our method with average accuracy of 97.5%.

The algorithm is further tested with another database (http://epileptologie-bonn.de). The power spectral values for 50 seizures and 50 non seizures EEG time-series have been tested. Of the 50 epileptic seizures, 45 are identified correctly and the remaining five segments are not

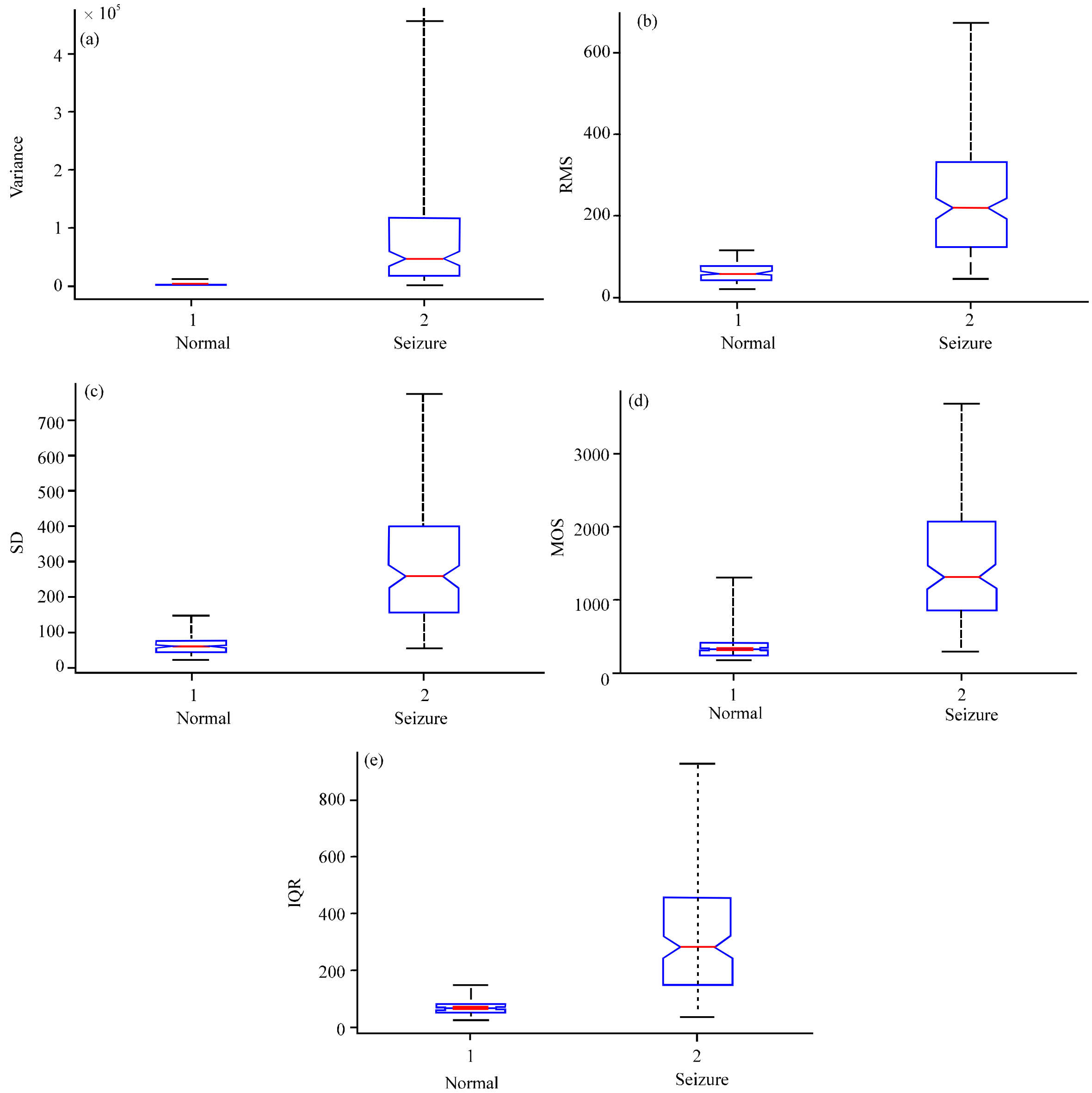

Fig. 9(a-e): Box plot obtained for 150 normal and 150 seizure segments

Table 5: Comparison of the results obtained by our method

Method	Accuracy	References
Chaotic measures	90.00	Kannathal *et al.* (2005a)
Entropy measure	92.22	Kannathal *et al.* (2005b)
Lyapunov exponents	96.79	Guler *et al.* (2005)
Discrete wavelet transform artificial neuro fuzzy network	85.90	Sadati *et al.* (2006)
Discrete wavelet transform	95.00	Subasi (2007)
Time frequency artificial neural network	97.72	Tzallas *et al.* (2007)
Fast ICA and neural network	71.25	Sivasankari and Thanushkodi (2009)
Time frequency analysis	94.50	Tzallas *et al.* (2009)
Wavelet coefficients	94.83	Ubeyli (2009)
Statistical measures	85.25	Bedeeuzzaman *et al.* (2009)
EEG Complexity and spectral analysis	98.33	Liang *et al.* (2010)
Eigensystem spectral estimation	97.50	Naghsh-Nilchi and Aghashahi (2010)
Sample entropy and extreme learning machine	95.67	Song and Lio (2010)
Spectral method and statistical analysis	97.50	Present study 2012

detected. It is also tested with 50 non seizure cases 46 are identified correctly and the remaining four segments are not saying correctly non seizure. These results are shown in the form of sensitivity, specificity and accuracy.

As expected, during the epileptic seizure activities, the magnitude of the spectral power increased. Box plots of the distributions of the normal EEG segments and the seizure segments are given in Table 2 and Fig. 7. There is an increase in the standard deviation during the seizure. Spectral method is applied here for single channel EEG segments since the seizure cases are generalized. The work can be extended to eight channels so that more insight into the localization of the seizure can be obtained. In the second method, statistical parameters are calculated for EEG signals for the datasets collected from two databases. The results of the investigation yields statistically significant differences in the parameters studied. The results shown in the Table 4 as statistical features namely variance, RMS, Standard Error Mean, Standard Deviation, Measure of Spread and Inter Quartile Range have statistically significant distribution for non seizure and during seizure. For the non seizure condition, the statistical feature values are considerably lower. The Box plots of the distribution of the statistical parameters are shown in Fig. 9.

The study of the large set of data with normal and seizure measures are plotted and tabulated using spectral and statistical methods.

CONCLUSION

The study presents automated detection technique of epileptic seizure activity based on spectral and statistical methods. The EEG signals from two databases are used here (Andrzejak *et al*., 2001 and http://epileptologie-bonn.de). We tested EEG segments each 150 signals with normal and seizure activity which yielded a sensitivity of 93%, the specificity of 97% and average accuracy of 95%.

The statistical features are analyzed and it is inferred that discrimination between normal and seizure segments can be performed in a better manner if these are included along with spectral features.

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