# Epilepsy Detection Using EEG Signals: A Review of Signal Processing and Machine Learning Techniques for Clinical Neurodiagnosis

**Dr. James Whitmore[1]***

[1]University College London, Institute of Neurology and Biomedical Engineering, London, United Kingdom

## ABSTRACT

Epilepsy is a brain disease which affects the near about 2-3% of world population. Electroencephalogram is used for the epilepsy detection which is the most economical and effective tool with high temporal resolution for understanding the complex dynamical behavior and studying physiological states of the brain. In this paper, epilepsy analysis methods are described on the basis of signal nature, linearity, distance measure & complex network analysis. Empirical mode decomposition is used for diagnosis of focal and non-focal epilepsy.

***Keywords***: *Electroerancephlogram (EEG), Epilepsy detection, Empirical Mode Decomposition (EMD).*

## I. INTRODUCTION

Human brain consists millions of neurons. Each neuron is responsible for human daily activities. Its firing generate a small amount of potential difference in human brain which is recorded by electroencephalogram .Brain is a complex structure any discontinuity in neurons generates physio pathological disorder. Epilepsy is neurological disorder which results of abnormal activity in brain. According to Acharya et.al. [1] in world 50 million people have epilepsy. There is two types of epilepsy disease: generalized and focal. On the research it is found that the near about 20% of patients with primary generalized epilepsy (in which effect on whole brain) and 60% of patients who have focal epilepsy (in which effect on a particular part of brain) [2].

Focal epilepsy is the form of epilepsy where onset of epilepsy occurs in the limited area of brain. Recording of signals from the brain area where the first ictal EEG signal changes are detected can be defined as “focal EEG signals”, other signals recorded from brain areas, not participating in seizure onset, known as “non-focal EEG signals” [2-3]. Localizing the area of focal epilepsy may be useful in presurgical analysis of it. Figure shows the difference between the generalized and focal epilepsy.

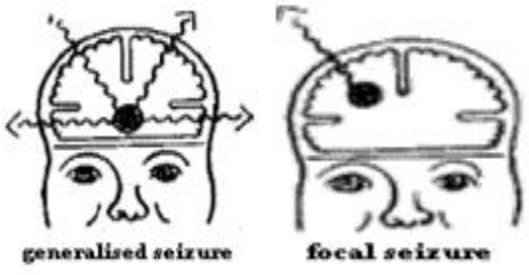


***Fig1: Effect of Generalized and focal Seizure***

During epileptic seizures major changes occur in a patient’s. By observing the symptoms one cannot judge the exact focal disease because there is also several disease which have same symptoms such as migraine, mental illness or narcolepsy; these are neurological disorder. Focal diseases also have two types simple and complex partial seizure. Generalized focal seizure has six types which are classified on the basis of their symptoms these are colonic, absence, myoclonic, tonic, tonic - clonic.

The electric activities in brain depend on the type of activity being done by a person. Brain waves are classified in different five categories (such as alpha, beta, gamma, delta, and theta) which provide information about state of mind and having a particular frequency range.

EEG provides a great facility to record the brain signal and comprises the seizure types. The recorded EEG signal more efficient for doctors to calculate near about 70-80% correct results of seizure presence or absence. EEG is noninvasive brain mapping method in which electrodes are placed on the scalp, very small amount of potential difference is recorded by the electrode and the signal are captured. To detect and analysis the signal, signal processing algorithm follows basically three steps:

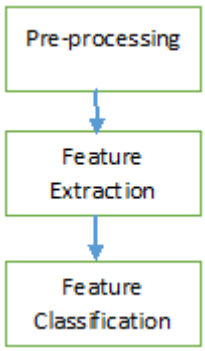


***Fig2: Basic Steps of Signal Processing Algorithm***

- Preprocessing: Noise is remove from the recorded EEG signal to get original Brain signal.
- Feature extraction: In these features such as entropy, energy, variance is extracted from the signal using Feature Extraction techniques.
- Feature classification: In these extracted signal classified into classes seizure and seizure free.

In present time classification is done by assuming the signal is non-stationary on the basis of this empirical mode decomposition(EMD), sample entropy, approximate entropy based method are developed.EMD is used for analysis of non-stationary and nonlinear signal. Intrinsic mode function (IMF) useful for empirical mode decomposition. On the basis of amplitude variation EEG signal is classified. High energy of EEG signal for a particular data points classify them in seizure and seizure free situation. Clustering coefficient of a complex network is used to predict epilepsy in local visibility graph method. Approximate entropy acts as feature extraction technique followed by the distance measure as post classifier by using correlation distance measure (CDM). [4]

## II. EPILEPSYANALYSISMETHOD

Seizure free classification purpose till now various algorithm based method are introduced ;on the basis of EEG signal nature, linearity and domain some methods are purposed by the authors, which are:

### A. Nature based method:

Recorded signal nature basis classification is done. EEG signal are stationary and non-stationary signal (Boshash, Meshab & et.al.) [5]. Considering signal is stationary in nature is old method for classification and principle component analysis method is used for this purposed.

- ***Principal component analysis (PCA) [6]:***

PCA is an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by some projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance. In PCA the extracted feature are linear [7].

- ***Independent Component Analysis (ICA)[6]:***

ICA assumes that each measured signal is a linear combination of independent signals. It decomposes multidimensional data vector linearly to statistically independent components. ICA can be effectively used to

remove artifacts and to decompose EEG recorded signals into different component signals originated from different sources [8] .In the context of epilepsy detection, ICA is used to extract the independent subcomponents corresponding to epileptic seizure from the mixture of EEG signals. The extracted subcomponents are then used to train classifiers that learn the difference between normaland epileptic segments.EEG signal can be input into a trained classifier to detect the presence of any seizure affected segments in it.

- ***Linear Discriminate Analysis (LDA):***

LDA is another commonly used technique for the reduction of dimensionality.LDA causes dimensionality reduction by finding a linear combination of features which can separate two or more classes. This linear combination can serve as a linear classifier. LDA models the difference between classes of data. LDA maximizes the ratio of variance between classes to the variance within class in the data set. LDA does not change the location of the original data sets, but provides more separation between classes. Subasi and Gursoy [9] used the time domain methods of PCA, ICA and LDA to reduce the dimensionality of frequency domain parameters for detecting epileptic EEG.

**B. Linearity based method:**

EEG signals are said to be nonlinear and non-stationary. On the basis of these for epilepsy analysis nonlinear parameter are used Such as Largest Lyapunov Exponent (LLE), Correlation Dimension (CD), Fractal Dimension (FD), Hurst Exponent (HE), entropies like Approximate Entropy (ApEn) and Sample Entropy (SampEn), and Recurrence Quantification Analysis (RQA) ;all these described by U. Acharya et.al. [6].Hereapproximate entropy and sample entropy is described.

- ***Approximate Entropy (ApEn)Varying Speed:***

The concept of approximate entropy is given by M. Pincus for system complexity [10].It used to quantify the complex nature of a particular time series. It's a measure of data regularity [1].If there is N data points, initial and original data points, The initial and original data points are written as;

$X = [x(1),x(2)....x(N)]$ (1)

m- vector points are X(1)….X

(N-m+1) is defined as follows

$X(i) = [x(i), x(i+1), \ldots . x(i+m-1)]$ (2)

Corresponding scalar components between *X (i*) and *X* (*j*), the maximum absolute difference is computed. Finally the similarity of patterns is computed as follows

$C_r^m(i) = \frac{M^m\ (i)}{N-m+1}$ (3)

Where,

m = window length; r = toleranceaverage of each frequency computed as

$C_r^m\ (r) = \frac{1}{N-m+1}\sum_{i-1}^{N-m+1} (\mathrm{r} - ||x(i) - x(j)||)$ (4)

$\varphi_r^m\ (r) = \frac{1}{N-m+1}\sum_{i-1}^{N-m+1} \ln C_r^m\ (i)$ (5)

Finally ApEn is computed as:[11]

ApEn (m,r,N) = $\varphi_r^m\ (r)$-$\varphi_r^{m+!}\ (r)$ (6)

Approximate entropy is used as feature extraction technique followed by the distance measure as post classifier epilepsy level is high (Prabhakar) [4].

- ***Sampled Entropy(SampEN): [12]***

It's a modified version of the ApEn. It is defined as the negative natural logarithm of the conditional probability that two sequence similar for same points remain similar at the next point, where self-match not included for computation [3]. The sampled entropy of IMF's have been used as a feature for discrimination between seizure and seizure free signal.The ApEn algorithm has not gone without scrutiny.Richman and Moorman [13]introduced SampEn as an algorithm to counteract the following shortcomings of ApEn.

1. ApEn inherently includes a bias towards regularity, as it will count a self-match of vectors.SampEn does not count a self-match, thus eliminating the bias towards regularity.
2. ApEn lacks relative consistency,as the input parameters are changed, the value of ApEn.
3. For computing sample entropy window length $m$& tolerance $r$ must be satisfied.Sample entropy algorithm is as [14]:
4. Step 1:Time-series data set of length N with a constant time interval X =[x(1),x(2)….x(N)]
5. Step 2: Define a template vector of length m, such that
$$X_m[i] = [x(i), x(i+1), \ldots . x(i+m-1)]$$
and the distance function $d\{x_m[i], x_m[j]\}$where (i≠j) between two vectors$x_m[i]$&$x_m[j]$.
6. Step 3:Count the number of vector pairs in template vectors of length m and m+1 having$d\{x_m[i], x_m[j]\} < r$and denote it by B and A respectively.

7. Step 4:Define the sample entropy to be as $SampEn = -log\frac{A}{B}$ (7)

Where; A= number of template vector pairs having $d\{x_m[i], x_m[j]\} < r$ of length m+1
B= number of template vector pairs having $d\{x_m[i], x_m[j]\} < r$ of length m

- ***Higher order spectra (HOS) [15]***

Higher order spectral analysis is a powerful tool for conducting nonlinear dynamical analysis of nonlinear, non-stationary and non-Gaussian physiological signals. HOS analysis can detect nonlinearity, deviations from Gaussianity and phase relationships between harmonic components of the signal.HOS are used to analyze signals and extract useful features which can be used to detect abnormalities. HOS (also called as polyspectra) is the spectral representation of higher order statistics, i.e. moments and cumulants of third and higher order. It can measure non-Gaussianity and separate non-Gaussian signal from an additive mixture of independent non-Gaussian signals and Gaussian noise using the property that HOS of Gaussian signals are statistically zero. The high noise immunity provided by HOS techniques is specifically useful in cases where the signals are corrupted with Gaussian noise. Another advantage is that HOS can preserve the true phase character of signals. Most of the work done so far in HOS used the third order statistics named bispectrum B(f1,f2) which is the third order cumulant generating function. It can also be defined as the FT of the third order correlation of a signal. It is given by

$$B(f1, f2) = E[X(f1)X(f2)X(f1+f2)] \quad (8)$$

Where:
X(f) = fouriertrasform of the signal X(nT); n = an integer index,T = the sampling interval and E[.] = the expectation operator

The expectation operator can be omitted for deterministic signals. For deterministic sampled signals, X(f) is the discrete-time FT computed using Fast Fourier Transform (FFT). From the equation, it can be seen that bi spectrum is a triple product evaluated at two frequencies and their sum frequency. Bi spectrum gives the cross correlation between frequency components in a two-dimensional frequency plot. The nonlinear interactions between harmonic components of a signal are thus clearly evident from the bi spectrum plot. Bi spectrum is a function of two frequencies whereas power spectrum is a function of one frequency variable.

- ***Largest Lyapunov Exponent (LLE) [6]***

Largest Lyapunov exponent is a measure of the dependence of the system on initial conditions. It defines the average rate by which two neighboring trajectories diverge or separate from one another. A negative exponent indicates that orbits approach a common fixed point, while azero exponent means that orbits maintain their relative positions. If a positive LLE is achieved, it indicates the existence of chaos in that system. It works on recorded time-series uses the nearest neighbor of each point in phase-space and traces their separation over certain time development. The LLE is then calculated by means of a least squares fit to the ‘‘average’’ line defined by:

$$y(i) = \frac{1}{\Delta t}(\ln dj(i)) \quad (9)$$

Here,
$dj(i)$ - represents the distance between each phase space point and its nearest neighbor at time step.

**C. Distance measure based method [4]**

- ***Euclidean Distance Measure:***

In a Euclidean space, the ordinary or the straight line distance between any two points is called as Euclidean distance (Macq &Cusierine) [16].It is sometimes referred to as Euclidean metric also. A Euclidean space is an affine space and it is not considered technically as a vector space. In a Euclidean structure, the inner product of real *n* - vectors (x and y) is computed as:

$$x.y = \sum_{i=1}^{n} xiyi = x1y1 + x2y2 + ..xnyn \text{ (10)}$$

In the Euclidean space, if the straight line distance between two points is considered and measured, then it becomes a metric space. The generalized associated norm is referred as Euclidean norm here. In a generalized manner, the Euclidean norm is represented as $L^2$norm or $L^2$distance.

Assuming that s = (s1,s2,….sn) and r = (r1,r2,…rn) the two points in Euclidean *n* space, then the corresponding distance from *s* to *r* , or from *r* to *s* is given by the Pythagorean formula as follows

$$d(s,r) = \sqrt{(r1 - s1)^2 + (r2 - s2)^2 + +(rn - sn)^2} \text{ (11)}$$

$$d(s,r) = \sqrt{\sum_{i=1}^{n}(ri - si)^2} \text{ (12)}$$

The Euclidean magnitude of a corresponding vector is nothing but the measurement of the length of the vector [8] and is expressed mathematically as follows:

$$||s|| = \sqrt{s1^2 + \cdots . + sn^2} = \sqrt{s.s} \text{ (13)}$$

Where(.) means the dot product

In single dimension plane, the distance between any two points on the real line is nothing but the absolute value of their numerical differences and is expressed as follows:

$$\sqrt{(x - y)^2} = |x - y| \text{ (14)}$$

- ***City Block Distance Measures***

If any two identical points are available, say for instance '*c*' and'd', with '*l*' dimensions, the City Block Distance Measures are calculated as follows:

$$\sum_{j=1}^{l} |cj - dj| \text{ (15)}$$

This distance cannot be less than zero and therefore it has to be only greater than or equal to zero [9].

- ***Correlation Distance Measures***

It is a measure of statistical independence between two random variables. It is not mandatory that both the random variables should have an equal dimension. The Distance Correlation of any two random variables is nothing but the ratio of the distance covariance to the product of their respective Standard deviations given by:

$$d\big(Cor(X,Y)\big) = \frac{dCor(X,Y)}{\sqrt{dVar(X)dVar(Y)}} \text{ (16)}$$

The $d\big(Cor(X,Y)\big)$ = 0 only if *X* and *Y* both are Independent variables. By simply substituting the sample distance covariance and distance variance, the distance correlation can be easily found out. Another important property of the distance correlation is that it must satisfy the following mathematical equations:

$$0 \le dCor(X,Y) \le 1$$

$$0 \le dCor(X,Y) \le 1$$

The dimensions of the original linear subspaces have to be satisfied by the distance correlation.

***Table 1: Different measure technique and their accuracy***

| Distance Measures | Accuracy |
|---|---|
| Euclidean | 85.31% |
| City Block | 86.74% |
| Correlation | 88.95% |

On the basis of different parameters such as performance index, specificity, sensitivity and accuracy epilepsy risk level is determined in which author found that the correlation distance measured is suitable. [4]

**D. Complex network**

The network topology of complex network is more complicated than the regular network. It include degree distribution, cluster coefficient, average distance, degrees-degree correlations, community structure and hierarchy etc. Using complex network analysis of EEG signals can shows the characteristics of brain electrical signal and clearly reflect the change and evolution process of brain electrical signal.

- ***Visibility Graph of Complex Networks***

Visibility graph method (VG) is a kind of one dimensional time series of the complex network construction method. Visibility graph method is to define each data point of the time series as network node and the connecting lines satisfied the visibility rules between data points is defined as the network connected edges [17].

Visibility rule: If (*tc,xc*) at any point between the two nodes (*ta*, *xa*) and (*tb* ,*xb*) *;* satisfied following condition:

$$\frac{xa-xc}{tc-ta} > \frac{xa-xb}{tb-ta} \quad (18)$$

The visibility is exists connected edges between two nodes.

- ***Local Visibility Graph Method [17]***

LVG is explained by Zhao Jiang et. al. [17] as:For a time series, set a sliding time window with the length L and the overlap length M. Connected edges exist when any two points in the sliding time window meet the visibility criterion. Thus the connected of the nodes in atime window of length L formed a local network. With the move of the sliding time window it can be constructed a number of local networks. With the time lapse, through the changes of the local networks in the time windows we can observe the time-dependent of the whole time series. By calculating the statistical features of each local network we get the time series evolution process. The local visibility graph can also achieve the result of the visibility graph. In this nodes are only connected with nodes in the time window. Compared with the visibility graph method to get a matrix, the local visibility graph remove some distant figure scattered points, and these are generally scattered some time apart longer points and have less time correlation.

**E. Empirical mode decomposition [18]**

Empirical mode decomposition (EMD) is a signal processing technique that represents any temporal signal into a finite set of amplitude and frequency modulated (AM-FM) oscillating components which are bases of the decomposition. The decomposition is an intuitive and adaptive signal- dependent decomposition. Moreover, the decomposition does not require any conditions about the stationary and linearity of the signal.The principle of the EMD technique is to decompose a complicated signal $x(t)$ iteratively into a set of the band-limited functions $Dm(t)$ named intrinsic mode functions (IMFs).Each IMF satisfies two basic conditions:

i. In the complete data set, the number of extrema and the number of zero crossings must be the same or differ at most by one,
ii. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The first condition is similar to the narrow-band requirement and the second condition is a local requirement induced from the global one, and necessary to ensure that the instantaneous frequency will not have redundant fluctuations as induced by asymmetric waveforms [19].The EMD algorithm for the signal $x(t)$ can be summarized as follows:

- Set
- Detect the extrema (both maxima and minima) of $g1(t)$.
- Generate the upper and lower envelopes $em(t)$ and $el(t)$, respectively by connecting themaxima and minima separately with cubic spline interpolation.
- Determine the local mean as: $m(t) = em(t) + el(t)$ (19)
- IMF should have zero local mean; subtract $m(t)$ from the original signal as: $g1(t) = g1(t) - m(t)$. (20)
- Decide whether $g1(t)$ is an IMF or not by checking the two basic conditions as described above.
- Repeat steps 2–6 and end when an IMF $g1(t)$ is obtained.

Once the first IMF is derived, define $D1(t) = g1(t)$, which is the smallest temporal scale in $x(t)$. To find the rest of the IMF components, generate the residue $r1(t)$ of the data by subtracting $D1(t)$ from the signal as:

$$r1(t) = x(t)\text{-}D1(t) \quad (21)$$

The shifting process will be continued until the final residue is a constant, a monotonic function, or a function with only maxima and one minima from which no more IMF can be derived. Thesubsequent basis functions and the residues are computed as,

$$r1(t)-D2(t)=r2(t),....,rM-1(t)-DM(t)=rM(t) \quad (22)$$

where$r\ M(t)$- is the final residue.

At the end of the decomposition the signal $x(t)$ is represented as follows:

$$x(t) = \sum_{m=1}^{n} Dm(t) + rM(t) \quad (23)$$

Where $M$ is the number of IMFs and $rM(t)$ is the final residue. Each IMF is assumed to yield a meaningful local frequency, and different IMFs do not exhibit the same frequency at the same time. Then aboveequation can be written as:

$$x(t) = \sum_{m=1}^{M} Am(t)\cos(\varphi m(t)) \quad (24)$$

EMD algorithm is explained by Pachoriet. al. By using empirical mode decomposition, the analytic IMFs can be mapped in to complex plane where trace has circular geometry with unique center. That makes the computation of area of IMFs feasible, covering significant number of total data points [18].

- ***Second-order difference plot***

The second order difference plot (SODP) of intrinsic mode functions of EEG signals can provide valuable diagnostic features for classification of ictal and seizure-free EEG signals. The SODP of signal $x(n)$ can be obtained by plotting $X(n)$ against $Y(n)$ which are defined as : The SODP is a graphical representation of successive rates against each other and provides rate of variability of data. Recently, the variability measured from the SODP has been used for analysis of EEG and center of pressure (COP) signal. SODP ofI MFs of EEG signals as a feature set for classification of ictal and seizure-free EEG signals.It is clear that the SODP of IMFs have epileptic patterns. It motivates to compute the ellipse area of SODP of IMFs for classification of ictal and seizure-free EEG signals.

## III. ANALYSIS OF DIFFERENT METHODS

Many authors used and proposed different methods for epilepsy detection also to differentiate generalized and focal signal by using EEG signal.

***Table 2 shows the summary of EEG signals feature and their methods:***

| Authors | Features | Classifier | Performance | Dataset |
|---|---|---|---|---|
| S.K. Prabhakar [4] | Approximate Entropy | Distance Measure | Accuracy 88.95%; PI 67.68 % | Coimbatore Hospital EDF format |
| Helen T. Ocbagabir [20] | Energy, Entropy, Variance | Linear Kernel SVM | Accuracy 95% | University of Bonn |
| MohmadFabi [21] | Signal Energy | Artificial Neural Network | Accuracy 100% | Available at [2] |
| SaadatNaheshi [22] | HAF & HOC | QDA & MD | GDR 91.44% | CHB Dataset |
| Rajeev Sharma [23] | 95 % Area Parameter of 2D PSR | Probilistic Neural Network (PNN) | Accuracy 98.67% | Available at [2] |

## IV. CONCLUSION

EEG signal used to detect the epilepsy disease. In this paper we focused on methods; on the basis of linearity, nature, correlation distance measure as classifier, network. These type of classification provide a visual knowledge of analysis of the EEG signal classification.

## REFERENCES


1. *U. R. Acharya, F. Molinarib, S. V. Sreec and S. Chattopadhyay, "Automated diagnosis of epileptic EEG using entropies," Elsevier, 2012, pp. 401-408.*
2. *R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David and C. E. Elge,"Indications of nonlinear deterministic and finite-dimensional structures in time series of brain state," Phys. Rev. E, vol. 64, 2001, pp. 1-8.*
3. *S. Gautam, R. B. Pachori and R. Sharma, "Focal &non focal Epilepsy Detection Using EEG Signals Via Empirical Mode Decomposition," IEEE, 2014, pp. 135-140.*
4. *S. K. Prabhakar and H. Rajguru, "Different Approach to Epilepsy Risk Level Classification Utilizing Various Distance Measures As Post Classifiers," in biomedical engineering international conference, 2015.*
5. *B. M. Boashas and M. Coltiz, "Time–frequency detection of EEG abnormilties," Elsiver, 2003.*
6. *U. R. Acharya, S. V. Sreec, S. G., R. J. Martis and J. S. Suri, "Automated EEG analysis of epilepsy: A review," Elsevier, 2013, pp. 147-155.*
7. *S. G. Dastidar, H. Adeli and N. Dadmehr, "Principal component analysis enhanced cosine radial basis function neural network for robust epilepsy and," in IEEE Trans. Biomed. Eng., 2008.*
8. *T. P. Jung, S. Makeig, M. Mckewon, A. Bell, T. Lee and T. Sejnowksi, "Imaging brain dynamics using independent component analysis," PROC IEEE, vol. 89, 2001, pp. 1104-1110.*
9. *A. I. Subasi and M. I. Gursoy, "EEG Signal classification using PCA, ICA," Expert Syst. Appl., vol. 12, 2010, pp. 8659-8664.*
10. *S. M. Pincus, "Approximate entropy as a measure of system complexity," Proc. Nati. Acad. Sci. USA, vol. 88, 1991, pp. 2297-2301.*
11. *H. Ocak, "Automatic detection of epileptic seizures inEEG using discrete wavelet transform and approximate Entropy", 2009, pp. 2027-2036.*
12. *Y. Song and P. Lio, "a new approach epileptic seziuredetection:Sample Entropy based feature extraction and extreme learning machine," J. Biomedical Science and Engineering, vol. 3, no. June 2010, pp. 556-567.*
13. *J. S. Richman and J. R. Moorman, "Physiological timeseries analysis using approximate entropy and sample entropy," in Am. J. Physiol. Heart Circ. Physiol, 2000.*
14. *R. B. Pachori and R. Sharma, "Application of sample entropy for discrimination between seziure and seziure free signal," in Fifth Indian International Conference on Artifical Intelligence, 2014.*
15. *C. L. Nikasis and A. P. Pertopulu, "Higher order Spectra Analysis:A Nonlinear signal Processing Framework," Englewood Cliffs, New Jerssy, 1993.*
16. *O. Cuisenarie and B. Macq, "Fast and exact signed Euclidean Distance transformation with linear complexity," in International Conference on Acoutics, Speech and Signal processing, 1999.*
17. *Z. Jiang, Y. Yanting and H. Chongqing, "Prediction of epilepsy disease based on complex network," International symposium on Computational IntelligianceAnd design, 2013, pp. 395-398.*
18. *V. B. Ram Bilas Pachori, "Analysis of normal and epileptic seizure EEG signals using empirical mode decomposition," Eliseive, 2011, pp. 373-381.*
19. *N. Huang, "The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time serise analysis," Proc. R.Soc. Lond., vol. A 354, 1998, pp. 903-995.*
20. *H. T. Octabgabir, A. B. Khalad and M. Faezipour, "EFFICIENT EEG ANALYSIS FOR SEIZURE MONITORING IN EPILEPTIC PATIENTS," IEEE, 2013.*
21. *M. Fani, G. Azmi and B. Boashash, "EEG Based Automatic Epilepsy Diganosis Using Instaneous Frequency With Sub Band Energies," in International Workshop On System,Signal Processing And Their Application, 2011.*
22. *A. E. SaadatNaheshi, "Online Epilepsy Diagnosis Based On Analysis Of EEG Signals By Hybrid Adaptive Filtering And High Ordered Crossing," in International Conference On Intelligent Computation And Bio-Medical Instrumentation, 2011.*
23. *R. B. P. Rajeev Sharma, "Classification Of Seizure And Seizure-Free EEG Signals Using Local Binary Patterns," Elsivier, vol. 42, 2015, pp. 1106-1117.*
24. *R. B. P. Rajeev sharma, "Classification of epileptic seziures in EEg Signals based on phase space representation of intrinsic mode function," Elsevier, 2015, pp. 1106-1117.*
25. *S. P. Ram Bilas Pachori, "Epileptic seizure classification in EEG signals usingsecond-order difference plot of intrinsic modefunctions," Elsevier, no. 2014, 2013,pp. 494-502.*
26. *V. Joshi, v. Antony and R. B. Pachori, "Classification of ictal and seziure free signal using fractional linear predication," Elsiver, vol. 9, 2014, pp. 1-5.*

27. *J. M. Yentes, N. Hunt, K. K. Schmid, J. P. Kaipust and D. Mcgrath, "The Appropriate Use of Approximate Entropy and Sample Entropy with Short Data Sets," Annals of Biomedical Engineering, 2012.*
28. *M. Cohen, D. Hudson and P. Deedwania, "Applying continuous chaotic modeling to cardic signal analysis," IEEE Engineering in Medicine and Biology Magazine, 1996, pp. 95-102.*
29. *T. S. Kumar, V. Kanhangad and R. B. Pachori, "Classification Of Seizure And Seizure free EEG Signals Using Local Binary Patterns," Elsevier, vol. 15, 2015, pp. 33-40.*