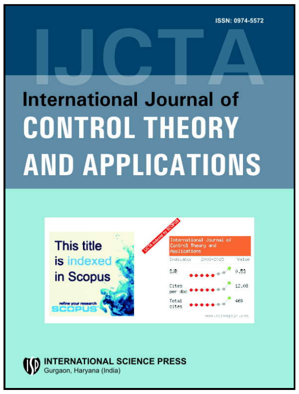

International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 6 • 2017

Classification of EEG Signals using Improved Probabilistic Fractal Dimension

Kunti Mishra[1] and Bhagwati Prasad[2]

[1] *Department of Mathematics Jaypee Institute of Information Technology, A-10, Sector-62, Noida, UP-201307 INDIA, Email: kuntimishra@gmail.com*
[2] *Department of Mathematics Jaypee Institute of Information Technology, A-10, Sector-62, Noida, UP-201307 INDIA, Email: b_prasad10@yahoo.com*

Abstract: Electroencephalogram (EEG) signals are used to detect neurological disorder like seizure, Alzheimer etc. In this paper, we classify EEG signals of epileptic seizure and seizure free patients using improved generalized fractal dimension(GFD). Different scales are obtained by taking different size of segments of the observed signals. Then the improved GFD is used to quantify the complexity of the signals. Statistical test also shows method provides better results in discriminating epileptic seizures than the GFD.

Keywords: Generalized fractal dimension, EEG signals, seizure, scale factor.

1. INTRODUCTION

Abnormality in behavior, loss of consciousness etc may be result of disturbance in nerve cell activity in human brain which results into neurological disorder. It may be epilepsy, but number of people without epilepsy may also have seizures. Electrical activity of the brain is recorded in the form of Electroencephalogram (EEG) signals. Whenever there is a neurological disorder, these signals also show some abnormality. This change in behavior of the signals helps in diagnosis of epileptic seizure. We find number of studies in literature regarding classification of such signals. They suggest different classification techniques, comparison of the techniques and combination of two or more schemes to differentiate epileptic EEG signals from the non epileptic one. These techniques include linear discriminant analysis, artificial neural network , wavelet transform, support vector machine, etc. (for example see [7], [10], [14] and [17]). These signals are non linear in nature. So, techniques from non linear dynamics and chaos theory such as correlation dimension, entropy, GFD are more efficient (for detail refer [11] and [12]. Main purpose of the present paper is to provide a better classification of epileptic EEG signals using improved GFD. First we, provide required background for GFD.

1.1. Fractal Theory

Mandelbrot noticed that the geometry of real life objects such as clouds, flowers, rivers, mountains etc. does not look like the existing conventional shapes in geometry. So, it is very difficult to model such irregular and non smooth objects [1]. Fractal geometry is introduced to deal with such problems. EEG signals also looks very irregular and self similar in nature. So, modeling of these type of signals becomes easy with the help of fractal geometry.

1.2. Fractal Dimension (FD)

Felix Hausdorff introduced the notion of FD, when he observed that repetitive nature of fractals, which is defined as

Definition 1 [13]. Let A be a subset of a Hausdorff space $H(X)$ other than empty set, where (X, d) is a metric space. For every $\varepsilon > 0$, if $N(A, \varepsilon)$ denotes the smallest number of closed balls of radius $\varepsilon > 0$, needed to cover A. Then Hausdorff dimension (HD) of A is given by

$$D = \lim_{\varepsilon \to 0} \left\{ \frac{\ln(N(A,\varepsilon))}{\ln(1/\varepsilon)} \right\},$$

if limit exists.

But problem with HD is its only applicabilty for exactly self similar objects. But in real life exact self similarity in object is rare. So, the concept of box counting dimension (BCD) is proposed to tackle such situation. BCD of any object A is calculated by covering the object with minimum boxes and observe how the number of minimum required boxes to cover the object changes with the size of the boxes. If

$$D = \frac{\ln(N(r))}{\ln(1/r)},$$

Then slope of D gives the numerical value of box counting dimension. Where, $N(r)$ is the lowest number of boxes of size r need to cover the object A.

Number of authors use box counting dimension as a diagnostic tool for different diseases like cervical cancer, brain tumors, Epileptic seizures etc. [5, 16]. Main disadvantage with the box counting dimension is that when we calculate it for any object, any box is counted or not counted at all, according to whether some points or no points exists in the box. It does not take into consideration number of points in the box counted. So, we still remain very far from the exact measurement of the dimension. For example, in Figure 1, we have two different shapes with same box counting dimension. Thus we still did not get the good classification.

Other methods also proposed by different authors to find fractal dimension named as information dimension, correlation dimension etc. Hentschel and Procacci [9] have proved that all these are special cases of generalized fractal dimension (GFD) defined as

Figure 1: Two different shapes with same box counting dimension (=1.74)

Definition 2 [18]. Let μ be the natural probability measure on the set A, and $B_l(x)$ be the ball of radius l centered about a point x on the set A. Then

$$D_q = \frac{1}{q-1} \lim_{r \to 0} \frac{1}{\log \ r} \log \int d\mu(x)(\mu B_l(x))^{q-1}.$$

Recently, Florindo and Bruno[6] proposed a classification scheme based on GFD for the texture analysis. Our basic aim is to provide an improvement of GFD which provide a better classification of EEG signals for the detection of epilepsy.

2. MATHEMATICAL ANALYSIS

First we put time series in the form of a square matrix, divide the matrix into boxes of the size $i \times i$ Let B_i denotes the i^{th} box and let $P_i = \mu(B_i)/\mu(A)$ be the normalized measure of this box. To practaically calculate D_q, we take natural probability measure is equivalent to the probability P_i, of any arbitrary point to be in i^{th} box B_i. For GFD, probability p_i is calculated as number of boxes containing i points divided by the maximum number of points inside a box [9]. But it does not take into account the signal value in time series or pixel intensity in any image. To improve generalized fractal dimension, we calculate it as:

$$p_i = \frac{\text{sum of signal values in } B_i}{\text{number of boxes} \times \text{maximum sum of signal values among all boxes}} \tag{1}$$

Generalized dimension for practical implementation is given by

Where, $\frac{1}{q-1} \lim_{r \to 0} \log_2 \sum_{i \in r} P_i^q$ is called generalized Renyi entropy. For $q = 0$, GFD becomes box counting dimension, for $q \to 1$, it tends to information dimension, for $q = 2$, it becomes correlation dimension and so on. In this way for any fractal we can have infinite number of generalized dimensions. Many authors use generalized dimension for the classification in different areas like satellite imagery, texture analysis etc. [3, 4, 6, 15]. Since this method is based upon probability, it is also called probabilistic fractal dimension.

3. DATA COLLECTION

To implement the method, we use EEG dataset available on line [2]. In the dataset, there are five sets A, B, C, D and E. Each set contains 100 text files. Each text file consists of 4096 samples of one EEG time series in ASCII code. Each signal is of 23.6 seconds duration. The sampling of the data is done at the rate of 173.61 Hz. Time series have the spectral bandwith of the aquisition system, which is 0.5 Hz to 85 Hz. We implement our method on set D and set E. Signals in D are from five seizure free patients, and signals in E are from seizure patients. In Figure 2, five signals from epileptic seizure patients and in Figure 3, five signals from seizure free patients are depicted.

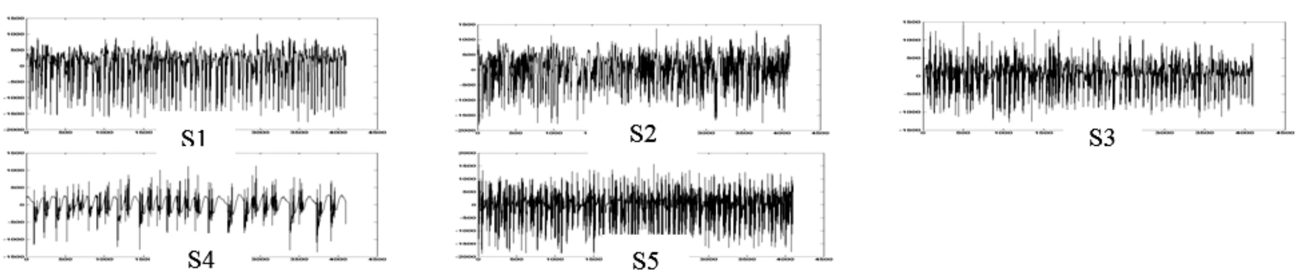

Figure 2. Example of signals from epileptic patients

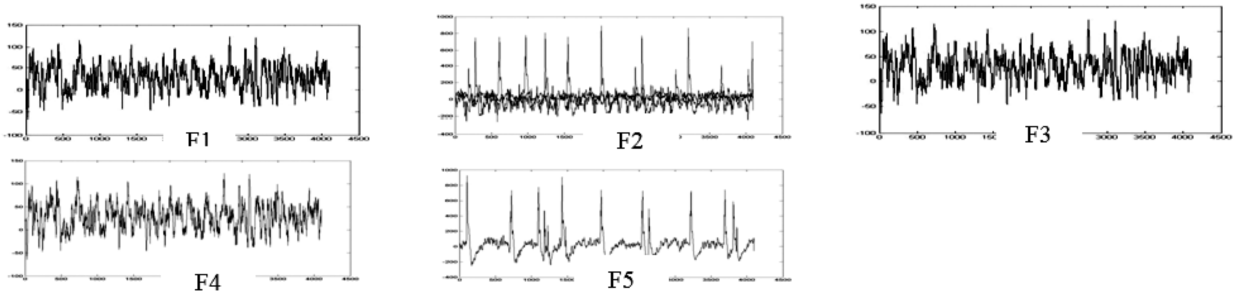

Figure 3: Example of signals from seizure free patients

4. RESULTS AND DISCUSSION

We apply GFD and Improved GFD to 100 signals from two data sets D and E contains signals from seizure free and seizure patients respectively. In our all calculations, we take $q \rightarrow 1$ i. e. information dimension. To compare the results of two methods, we randomly select five sample signals from epileptic seizure and five from seizure free signals, shown in Figure 2 and Figure 3. In Figure 4 and Figure 5, we plot improved generalized Renyi entropy and generalized Renyi Entropy versus log r respectively for sample signals. If we compare the plots of Figure 4 with Figure 5, we see that improved generalized fractal dimension performs better at all scales.

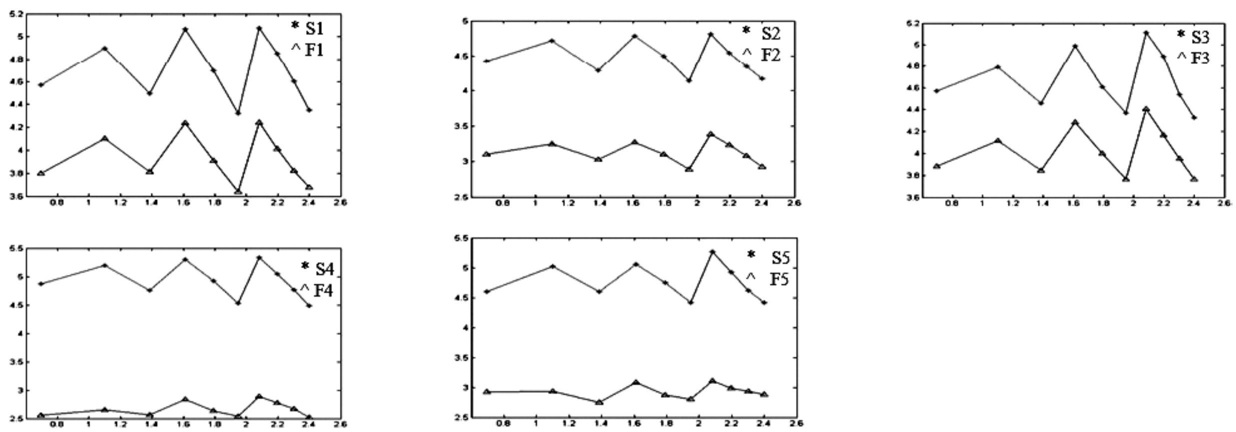

Figure 4: Improved generalized Renyi Entropy verus log r for both seizure and seizure free signals

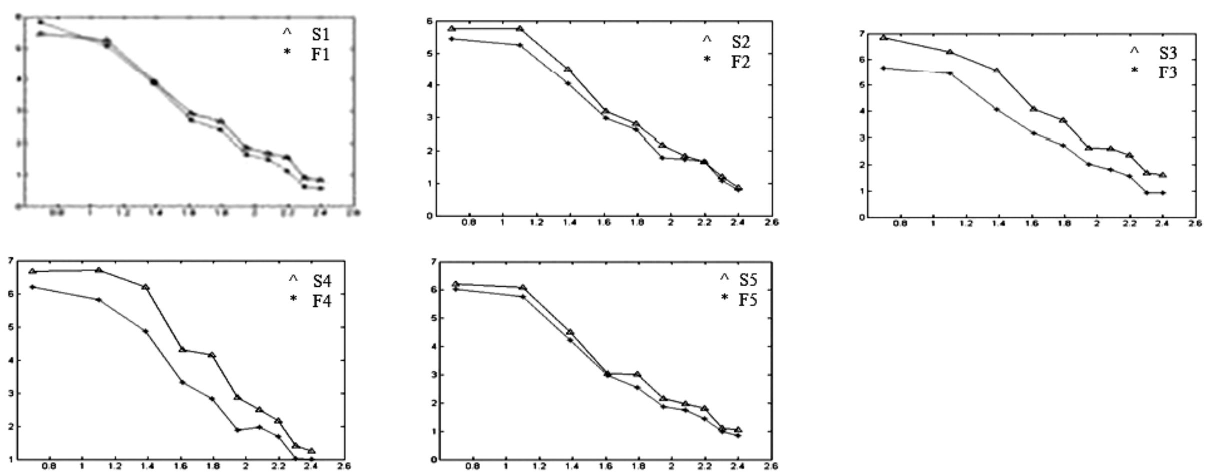

Figure 5: Generalized Renyi Entropy verus log r for both seizure and seizure free signals

As we know, in case of asymmetric populations, performance of the non-parametric Kruskal-Wallis test is better than the parametric equivalent Anova test.[8]. So, for statistical comparison of the classification results obtained from two methods, we apply Kruskal-Wallis test. First, we put Improved GFD of seizure data in column 1 and seizure free in column 2 for 100 signals then apply Kruskal Wallis test for the two columns. Test of Classification results on sample signals for improved GFD is given in table 1 and for GFD in table 2. As we can see p-values in table 2 are greater than the p-values in table 1 correspondingly. We also draw Box plots for the same as shown in Figure 6 and Figure 7. So, Kruskal wallis test also indicates that the classification by improved GFD is better than the GFD.

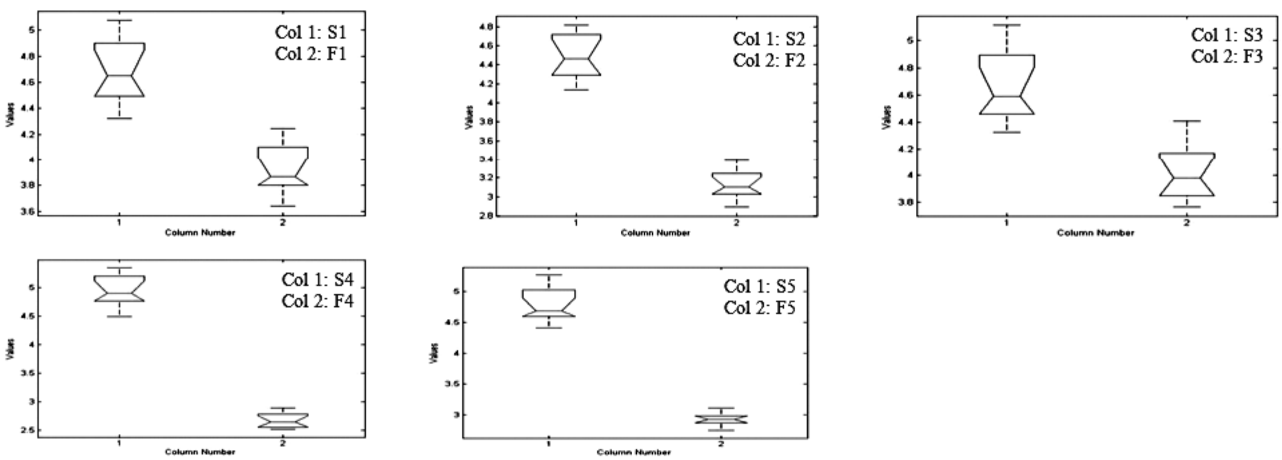

Figure 6: Box plots for seizure and seizure free EEGs for improved GFD

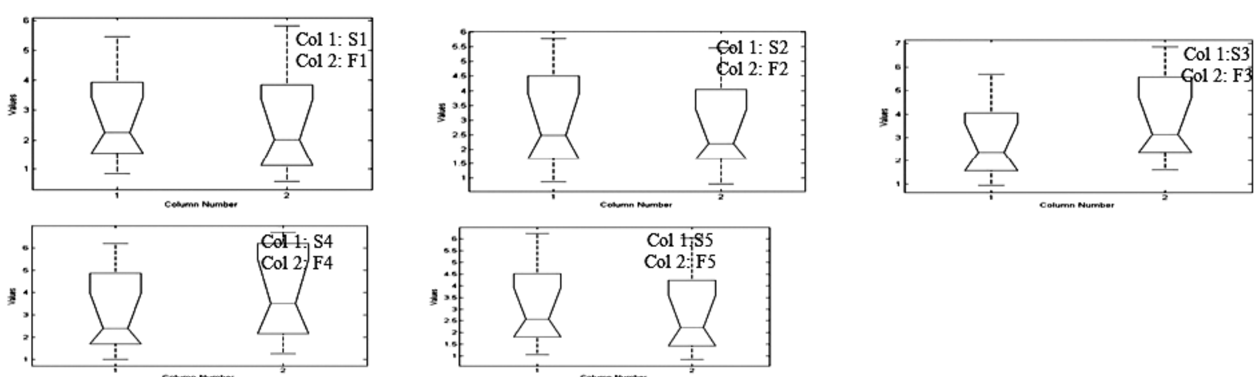

Figure 7: Box plots for seizure and seizure free EEGs for GFD

Table 1
Kruskal Wallis Anova Table for GFD of seizure and seizure free signals

Source	*SS*	*DF*	*MS*	*Chi-sq*	*Prob > Chi-sq*
1. S1 and F1					
Col	500	1	500	14.29	0.0002
Error	165	18	9.1667		
Total	665	19			
2. S2 and F2					
Col	500	1	500	14.29	0.0002
Error	165	18	9.1667		
Total	665	19			

3. S3 and F3					
Col	460.8	1	460.8	13.17	0.0003
Error	204.2	18	11.344		
Total	665	19			
4. S4 and F4					
Col	500	1	500	14.29	0.0002
Error	165	18	9.1667		
Total	665	19			
5. S5 and F5					
Col	500	1	500	14.29	0.0002
Error	165	18	9.1667		
Total	665	19			

Source	*SS*	*DF*	*MS*	*Chi-sq*	*Prob > Chi-sq*
1. S1 and F1					
Col	9.8	1	9.8	0.28	0.5967
Error	655.2	18	36.4		
Total	665	19			
2. S2 and F2					
Col	7.2	1	7.2	0.21	0.6501
Error	657.8	18	36.5444		
Total	665	19			
3. S3 and F3					
Col	45	1	45	1.29	0.2568
Error	620	18	34.4444		
Total	665	19			
4. S4 and F4					
Col	39.2	1	39.2	1.12	0.2899
Error	625.8	18	34.7667		
Total	665	19			
5. S5 and F5					
Col	20	1	20	0.57	0.4497
Error	645	18	35.8333		
Total	665	19			

SS = sum of squares, MS = mean of squares, DF = degree of freedom, Chi-sq = Chi-square value, Col=Columns

5. CONCLUSION

We propose an improved version of multi-scale generalized fractal dimension method for extracting descriptors to characterize EEG signals obtained from the patients with seizure and without seizure. We compare efficiency of the technique with the classical GFD. Results verify that the improved GFD provide better classification at all scales. To statistically verify it, we apply Kruskal Walli's test on the GFD and improved GFD. Box plots and Anova tables indicate the efficiency of the improved GFD over GFD. This method may also provide excellent result for other bio medical signals also. Moreover, This method can also be used for the classification in other areas like speech recognition, human motion analysis, handwriting analysis, etc.

REFERENCES

[1] Andres, J. and J. Fišer, *Metric and topological multivalued fractals.* International Journal of Bifurcation and Chaos, 2004. **14**(04): p. 1277-1289.

[2] Andrzejak, R.G., K. Lehnertz, F. Mormann, C. Rieke, P. David, and C.E. Elger, *Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state.* Physical Review E, 2001. **64**(6): p. 061907.

[3] Backes, A.R. and O.M. Bruno, *Fractal and Multi-Scale Fractal Dimension analysis: a comparative study of Bouligand-Minkowski method.* INFOCOMP Journal of Computer Science, 2008. **7**(2): p. 74-83.

[4] Backes, A.R. and O.M. Bruno. *Plant leaf identification using multi-scale fractal dimension.* in *International Conference On Image Analysis And Processing.* 2009: Springer.

[5] Barry, D.J., *Quantifying the branching frequency of virtual filamentous microbes using fractal analysis.* Biotechnology and bioengineering, 2013. **110**(2): p. 437-447.

[6] Florindo, J.B. and O.M. Bruno, *Fractal descriptors based on the probability dimension: a texture analysis and classification approach.* Pattern Recognition Letters, 2014. **42**: p. 107-114.

[7] Güler, N.F., E.D. Übeyli, and I. Güler, *Recurrent neural networks employing Lyapunov exponents for EEG signals classification.* Expert systems with applications, 2005. **29**(3): p. 506-514.

[8] Hecke, T.V., *Power study of anova versus Kruskal-Wallis test.* Journal of Statistics and Management Systems, 2012. **15**(2-3): p. 241-247.

[9] Hentschel, H. and I. Procaccia, *The infinite number of generalized dimensions of fractals and strange attractors.* Physica D: Nonlinear Phenomena, 1983. **8**(3): p. 435-444.

[10] Joshi, V., R.B. Pachori, and A. Vijesh, *Classification of ictal and seizure-free EEG signals using fractional linear prediction.* Biomedical Signal Processing and Control, 2014. **9**: p. 1-5.

[11] Kannathal, N., M.L. Choo, U.R. Acharya, and P. Sadasivan, *Entropies for detection of epilepsy in EEG.* Computer methods and programs in biomedicine, 2005. **80**(3): p. 187-194.

[12] Lerner, D.E., *Monitoring changing dynamics with correlation integrals: case study of an epileptic seizure.* Physica D: Nonlinear Phenomena, 1996. **97**(4): p. 563-576.

[13] Mandelbrot, B.B., *The fractal geometry of nature.* Vol. 173. 1983: Macmillan.

[14] McSharry, P.E., T. He, L.A. Smith, and L. Tarassenko, *Linear and non-linear methods for automatic seizure detection in scalp electro-encephalogram recordings.* Medical and Biological Engineering and Computing, 2002. **40**(4): p. 447-461.

[15] Parrinello, T. and R. Vaughan, *Multifractal analysis and feature extraction in satellite imagery.* International Journal of Remote Sensing, 2002. **23**(9): p. 1799-1825.

[16] Rajagopalan, V., Z. Liu, D. Allexandre, L. Zhang, X.-F. Wang, E.P. Pioro, and G.H. Yue, *Brain white matter shape changes in amyotrophic lateral sclerosis (ALS): a fractal dimension study.* PloS one, 2013. **8**(9): p. e73614.

[17] Subasi, A., *EEG signal classification using wavelet feature extraction and a mixture of expert model.* Expert Systems with Applications, 2007. **32**(4): p. 1084-1093.

[18] Theiler, J., *Estimating fractal dimension.* JOSA A, 1990. **7**(6): p. 1055-1073.