Graph Signal Processing of EEG signals for Detection of Epilepsy

* Priyanka Mathur
Dept. of Electrical Engineering
Shiv Nadar University
Greater Noida, India
pm133@snu.edu.in

Vijay Kumar Chakka
Dept. of Electrical Engineering
Shiv Nadar University
Greater Noida, India
vijay.chakka@snu.edu.in

***Abstract*—Epileptic Seizure is a chronic nervous system disorder which is analyzed using Electroencephalogram (EEG) signals. This paper proposes a Graph Signal Processing technique called Graph Discrete Fourier Transform (GDFT) for the detection of epilepsy. EEG data points are projected on the Eigen space of Laplacian matrix of graph to produce GDFT coefficients. The Laplacian matrix is generated from weighted visibility graph constructed from EEG signals. It proposes Gaussian kernel based edge weights between the nodes. The proposed GDFT based feature vectors are then used to detect the seizure class from the given EEG signal using a crisp rule based classification. Simulation results show that the proposed GDFT based features from Gaussian Weighted Visibility Graph (VG) can detect epileptic seizure with 100 % accuracy.**

Keywords— Epilepsy, EEG, Gaussian kernel function, Graph Discrete Fourier Transform (GDFT), Weighted Visibility Graph.

I. INTRODUCTION

Graph Signal Processing (GSP) studies the signals having irregular domain residing on the nodes of a graph instead of regular intervals such as grids. To provide a nice compact format to encode the structure within the data, new tools are being developed in GSP [1]. Among various fields such as social network, gesture recognition, road network etc. Human Brain provides structure which can be easily analysed in graph signal domain. It provides the most inclusive information of psychological state of -a person. Epilepsy is one such kind of seizure that affects various psychological and physical functions. It is a neurological disorder where sudden abnormal reactions occur in the brain producing fluctuations which are captured in EEG signals.

Earlier epilepsy was detected manually by inspection of EEG signals. To automate the process of detection of epilepsy, numerous techniques have been developed [3-7]. In the current era, graph signal processing techniques are emerging fields to analyze the brain signals. One such graph signal based visibility graph technique provides methods to capture the chaotic nature of EEG signals [2]. This VG based method has encouraged us to present a new epilepsy detection method.

This work proposes Graph Discrete Fourier Transform (GDFT) based features of EEG signals defined on VG . The main contributions of this paper includes the following:

1) Proposed a Gaussian kernel based method for defining a unique weight to the edges of the visibility graph obtained from EEG time series data.

2) Proposed a Graph Discrete Fourier Transform based technique for obtaining features which are used for detecting epilepsy class in EEG Signals.

The rest of this paper is organized as follows: A brief review of the related work in the area of detection of epilepsy is given in section II. Section III presents system overview and our methodology in detail. Section IV deals with simulation results on publicly available EEG database and finally Section V concludes the paper and provides the future avenues.

II. PROLOGUE ASSESSMENT

Epileptic seizure in EEG signal using graph based techniques involves conversion of the time series signal into a complex graph. One such mapping called Visibility Graph (VG) method is proposed by Lacasa et al. [2]. To provide different strength to the edges of the graph, several techniques have been developed to construct Weighted Visibility Graph [3-5]. Supriya et al. [4] proposed an edge weight given in radian function which is the angle between connected nodes measured by using arc tangent. To improve the detection rate of epilepsy, various features that can be extracted from the graph have been proposed like entropy as given by Mohammadpoory et al. [6].

Further graph signal processing is applied to brain signals in fMRI data for feature extraction as given by Huang et al. [9]. Rui et al.in [10] explored graph signal processing for dimensionality reduction. In addition, neural networks for graph signals have been considered for analysis of MEG signals as in Guo et al. [11] and fMRI signals by Ktena et al. [12]. However, GDFT based method for detection and classification of epilepsy in EEG signals is not explored prominently.

The paper proposes a new edge weights for visibility graph of EEG signals by using Gaussian kernel function. This weight function provides unique value to each edge thereby capturing sudden fluctuations happening in EEG during seizure activity. Further by calculating Laplacian Eigen vectors from weighted graph, Graph Discrete Fourier Transform (GDFT) is applied on EEG signals. Thus, each EEG graph signal is projected on the Eigen space of the Laplacian matrix and produces a unique set of GDFT coefficients. Power Spectral Density (PSD) of GDFT coefficients is calculated which serves as feature vector for classification. The proposed feature set is then classified using crisp rule based classification with predefined threshold value of PSD. Thus, GDFT based features for different EEG signals will provide attributes that can precisely classify the EEG data for epilepsy.

Simulation results performed on the EEG database were able to detect the epilepsy class from EEG signals. Our method is quite effective with minimum complexity as only a crisp rule based classification results in the detection of epileptic seizure with 100% accuracy.

III. METHODOLOGY

A. System overview

The proposed algorithm is divided in various sections to understand it in a better way.

- Initially time series EEG signal is converted into visibility graph and weights are assigned to the connected edges using Gaussian kernel function.
- Graph Discrete Fourier Transform is then applied using Eigen vectors of Laplacian matrix obtained from weighted graph.
- Power Spectral Density (PSD) is calculated from GDFT coefficients which finally serves as feature vector for classifying EEG signals.
- The classification is performed by applying a crisp rule based classifier using a threshold value to distinguish normal class of EEG signal from ictal epileptic class.

Fig. 1 outlines the block diagram of our method of detection of epilepsy from EEG time series signal.

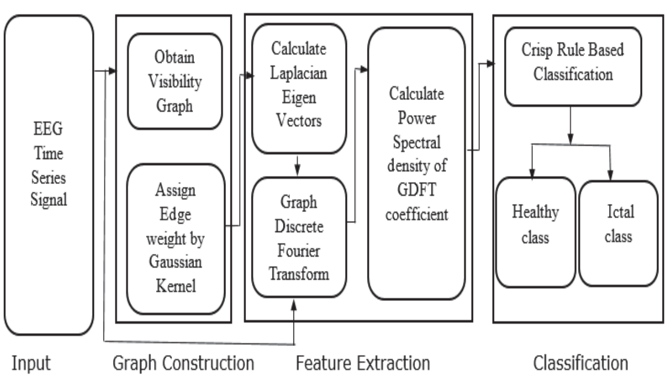


Fig. 1. System Architecture of proposed approach

B. Mapping of Time series into Gaussian kernel Weighted Visibility Graph

1.Visibility Graph: EEG time series data is mapped into visibility graph. A graph is defined by a set of nodes connected by the set of edges. Each EEG data point in time series in considered as a node and edges between the nodes is determined by visibility graph approach.

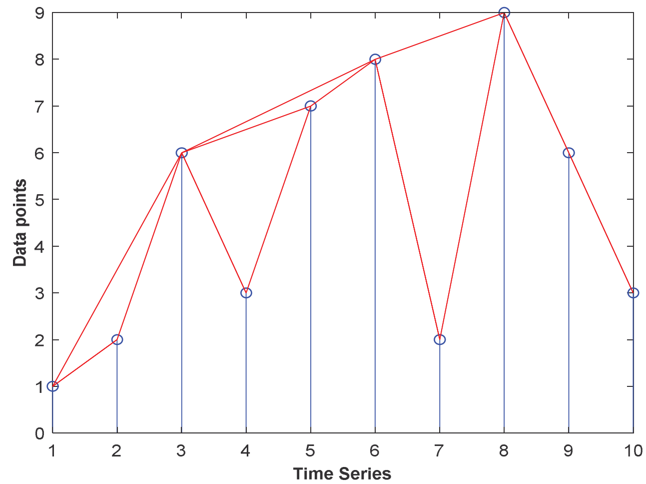


Fig. 2. Visibility Graph example where graph is shown in red

In the VG method, each data point corresponds to a node in the graph. An edge exist between node x_i and x_j if there is no other node in-between the visibility of the nodes. An edge can exist between the time instant t_i and t_j with data point x_i and x_j, using following criteria for the intermediate node x_k at t_k.

$$x(t_k) < x(t_i) + \left(x(t_j) - x(t_i)\right)\frac{t_k - t_i}{t_j - t_k} \ ; \ i < k < j \quad (1)$$

Fig. 2 shows the example of a visibility graph constructed from time series data.

2.Assigning Edge weight: The edge weights are chosen as a nonlinear Gaussian function of Euclidean distance between the nodes i and j, i.e. dist. (i, j) satisfying the visibility conditions given in (2). The standard deviation (σ) helps us to localize or globalize the processing. By keeping the sigma less than one, we can localize the processing whereas by taking sigma greater than one, we may turn it into global processing for a same Euclidean distances. The objective of detecting the sudden fluctuations that occur during Epileptic seizure attacks is achieved by choosing standard deviation less than one. In this paper we have calculated the edge weights for the visibility graph by using Gaussian kernel function defined as follows using σ as 0.5.

$$W_{ij} = \left\{ \exp\left(\frac{-|dist(i,j)|^2}{2\sigma^2}\right) : \text{if edge between i, j exists} \quad (2)\right.$$

C. Feature Extraction

The Laplacian matrix (L) is another characterization of weighted graph (W). The advantage of using Laplacian matrix characterization on weighted adjacency matrix is that former results in positive Eigen values, whereas in latter one may have both positive and negative Eigen values. So we are using Laplacian matrix characterization as defined below.

$$L = D - W \tag{3}$$

where D denotes a diagonal matrix which indicates the degree in terms of total edge weights at each node

$$D_{ii} = \sum_{j=1}^{N} W_{ij} \tag{4}$$

EEG signal is now a graph signal X, defined on the nodes of the graph. The Graph Discrete Fourier transform (GDFT) of a signal is projection of this signal X on the Eigen vectors of Laplacian matrix of the graph i.e. on columns of U matrix as defined below (5).
The GDFT coefficients represent the similarity (dot product) of X with each column of Eigen vectors.

$$X_{GDFT} = U^{H} X \tag{5}$$

where U^H denotes the hermition matrix of U and X_{GDFT} is the GDFT coefficients of each signal. These GDFT coefficients are further used to extract feature descriptors for detection of epilepsy. We calculate the Power Spectral Density (PSD) given by (6) of GDFT coefficients to form the feature vector which is finally fed to the crisp rule based classifier.

$$PSD = \frac{\left(\sum_{i=1}^{N} |X_{GDFT(i)}|^2\right)}{N} \tag{6}$$

where N denotes the number of nodes in the graph. Fig. 3 shows the boxplot of the feature vector obtained from PSD values of GDFT coefficients. It is clear from the boxplot that PSD feature value of GDFT coefficients of ictal class of epilepsy is higher than those of healthy class. Thus this feature is able to perfectly capture the disparity between epileptic and healthy class. This motivated us to use a simple crisp rule based classifier using a threshold to distinguish ictal and healthy class of EEG signals. This saves the complexity involved in training the complex machine learning based classifier.

D. Crisp Rule Based Classification

The crisp rule based classification technique classifies the EEG signals into their appropriate classes on the basis of a threshold value. It is a knowledge based model which has set of predefined thresholds for detecting epileptic class. In this work, threshold is determined by taking the mean of uniformly distributed random samples of PSD.

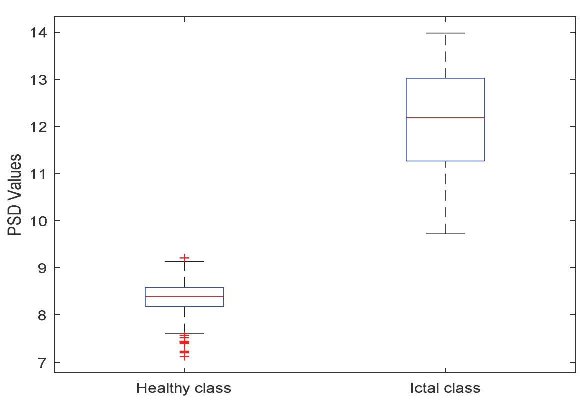


Fig. 3. Boxplot of PSD of GDFT coefficients

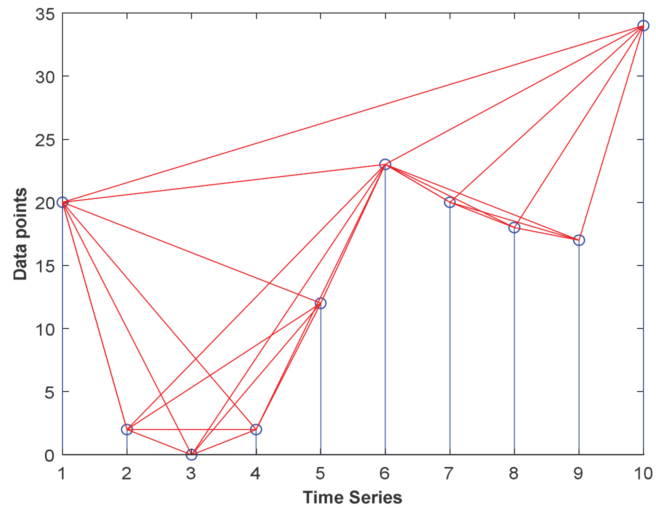


Fig. 4. Visibility Graph of epileptic seizure (ictal) class

Thus feature set of those class which is above the threshold belong to one category and other belong to second category of signals.

IV. RESULTS AND DISCUSSION

A. Database:

Our proposed epilepsy detection method using graph signal is tested on online available EEG database provided by center for epilepsy in University of Bonn, Germany [14]. The database consists of 100 samples from each group of EEG signal [5]. In this paper, we have used two groups of database (healthy (Set A), and epileptic (ictal set E) to evaluate the performance of our proposed methodology. We have used 2000 sample points from each signal to generate Gaussian Weighted Visibility Graph by keeping value of sigma as 0.5.

The proposed technique is implemented on MATLAB. Fig. 4 shows example of visibility graph of EEG signal using 10 data points from ictal set E.

For feature extraction, we have applied GDFT to the EEG graph signal and obtained power spectral density as feature vector of each weighted graph. The crisp rule based classifier separates the given feature vector of 200 samples into two classes: ictal and healthy thereby detecting the epileptic seizure in EEG signal.

B. Performance evaluation:

To check the performance of proposed technique, we have used the following parameters:
1. Sensitivity: which defines probability of positive results in case of correct class of sample.

$$Sensitivity = \frac{True\ \ Positive}{True\ Positive + False\ Negative}$$

2. Specificity gives the probability of negative result in case of incorrect class of sample

$$Specificity = \frac{True\ \ Negative}{True\ Negative + False\ Positive}$$

3. Accuracy is the ratio of the correct class of samples to the total number of samples

$$Accuracy = \frac{True\ Positive + False\ Negative}{True\ Positive + False\ Negative + True\ Negative\ \ + False\ Positive}$$

where, True Positive indicates correctly classified healthy class, True Negative is the correctly classified epileptic class, False Positive measures the false detection of healthy class, and False Negative gives falsely detected epileptic class in EEG data. In this paper, 100 % accuracy is achieved using threshold based classification with proposed technique for detection of epilepsy in EEG database.

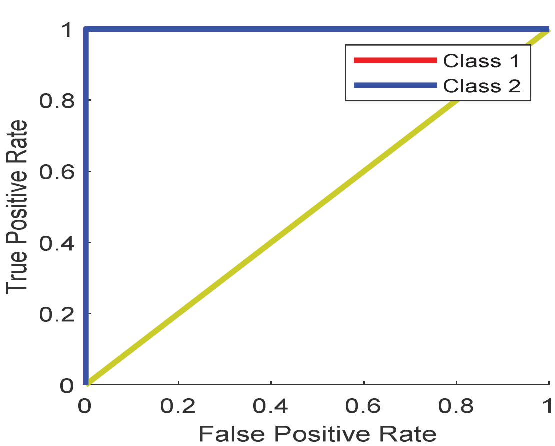
Further we have compared our technique of GDFT based features with the entropy feature [6] used by the researchers on visibility graph of EEG signals with the same database using K Nearest Neighbor (KNN) classifier. Performance of proposed features with above measures is tested using ten-fold cross-validation technique .With KNN classifier also, the proposed method achieves 100% accuracy.

Table I. summarizes the comparative analysis of our proposed method with existing technique using above performance measures.

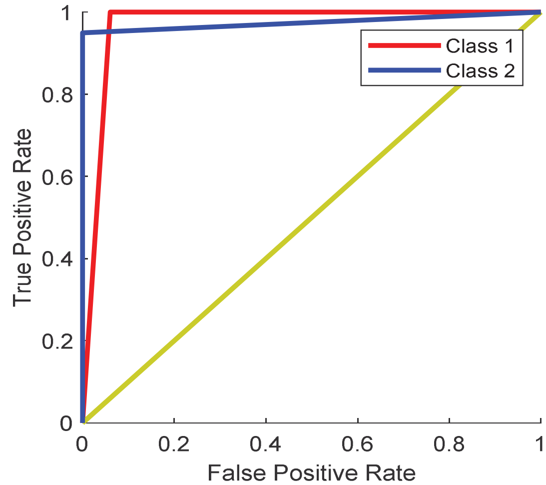
TABLE I. COMPARISON BETWEEN PROPOSED METHOD WITH ENTROPY BASED METHOD

Methods	Sensitivity (%)	Specificity (%)	Accuracy (%)
Proposed	100	100	100
Entropy based method	95.23	97.34	96.7

The above analysis reveals that proposed technique performs better than the entropy based technique for detection of epilepsy using visibility graph of EEG signals.



(a)



(b)

Fig. 5. ROC curve (a) Proposed GDFT based features (b) Entropy based features

Fig. 5 displays the ROC curve of classification using proposed method where number of true positive case is 100% both for class 1(healthy) and class 2 (ictal class) as compared to 95 % true positive rate for class 1 with false positive rate of 6% for class 2 in entropy based method.

Further we have compared the results of our weighted visibility graph with existing entropy features and summarized the results in Table II. It clearly indicated that our method of assignment of weight improves the classification results of visibility graph entropy based methods. Thus our proposed method of Gaussian weighted visibility graph approach with graph signal processing technique to calculate GDFT coefficient based feature vector is more accurate than the existing weighted VG-based entropy methods.

TABLE II. COMPARISON BETWEEN PROPOSED GAUSSIAN WEIGHTED VG WITH ANOTEHR WEIGHTED VG ENTROPY

Methods	Sensitivity (%)	Specificity (%)	Accuracy (%)
Proposed method	95	100	97.5
Entropy based method	95.23	97.34	96.7

V. CONCLUSION AND FUTURE WORK

This paper presented a novel method for detecting epilepsy in EEG signals using Graph Discrete Fourier Transform (GDFT) based features from Gaussian kernel edge weight in the visibility graph. Highly accurate and easy to calculate PSD features are classified using a simple rule based classifier using a pre-defined threshold to detect ictal class of epilepsy from EEG signals. The experimental results show that the proposed features produced can detect epilepsy with

100% accuracy. Future Avenue of the proposed method is to compare the performance of the proposed method with other non VG based methods. Further the concept of Graph Signal Processing will be extended for detecting other brain disorders and in diffusion modelling of brain signals.

REFERENCES

[1] G. D. I. Shuman, S. K. Narang, P. Frossard, A. Ortega, and P. Vandergheynst, “The emerging field of signal processing on graphs: Extending high dimensional data analysis to networks and other irregular domains,” Signal Processing Magazine, IEEE, vol. 30, no.3, pp. 83-98, 2013.

[2] L.Lacasa, B. Luque ,F Ballesteros ,J Luque , Nuno JC. “From time series to complex networks: the visibility graph. “ Proceedings of National Academy of Science, vol. 105, no 13, pp. 4972-4975, 2008.

[3] G. Zhu, Y. Li and P. Wen, "Epileptic seizure detection in EEGs signals using a fast weighted horizontal visibility algorithm", Computer Methods and Programs in Biomedicine, vol. 115, no. 2, pp. 64-75, 2014.

[4] S. Supriya, S. Siuly and Y. Zhang, “Automatic epilepsy detection from EEG introducing a new edge weight method in the complex network,” IET Electronics Letters, vol. 52, Issue 17, pp. 1430–143, August 2016.

[5] S. Supriya , S Siuly, W Hua “ Weighted visibility graph with complex network features in the detection of epilepsy,” IEEE Access vol..4, pp.6554–6566, 2016.

[6] Z. Mohammadpoory, M. Nasrolahzadeh, J.Haddadnia,“Epileptic Seisure detection in EEGs signals based on the weighted visibility graph entropy “, Seizure - European Journal of Epilepsy Elsievier, vol.. 50, pp. 202-208, August 2017.

[7] MethS. Siuly ,H. Wang and Y. Zhang, " Analyzing EEG signal data for detection of epileptic seizure: Introducing Weight on Visibility Graph with Complex Network Feature ", Australasian Database Conference (ADC 2016), Sydney, 2016.

[8] A. Sandryhaila and J. M. F. Moura, “Discrete signal processing on graphs: Graph Fourier Transform”, ICASSP, pp. 6167-6170, 2013.

[9] W. Huang, L. Goldsberry, N. F. Wymbs, S. T. Grafton, D. S. Bassett, and A. Ribeiro, “Graph frequency analysis of brain signals,” IEEE Journal of Selected Topics in Signal Processing, vol. 10, no. 7, pp. 1189–1203, 2016.

[10] L. Rui, H. Nejati, and N.-M. Cheung, “Dimensionality reduction of brain imaging data using graph signal processing,” in Proceedings of International Conference on Image Processing, pp. 1329–1333, 2016

[11] Y. Guo, H. Nejati, and N.-M. Cheung, “Deep neural networks on graph signals for brain imaging analysis,” Proceedings of 2017 IEEE International Conference on Image Processing (ICIP) ,pp 3295-3299,2017.

[12] S. I. Ktena et. al Parisot, E. Ferrante, M. Rajchl, M. Lee, B. Glocker, and D. Rueckert, “Distance metric learning using graph convolutional networks: Application to functional brain networks.In: Descoteaux M et.al, Medical Image Computing and Computer Assisted Intervention − MICCAI 2017, Lecture Notes in Computer Science, vol. 10433. Springer, 2017.

[13] J Shukla, V. K. Chakka, A. Satyanarayana Reddy, and Madan Gopal,” Graph Fourier Transform Based Descriptor for Gesture Classification”, Proceedings of IEEE, 2017 Fourth International Conference on Image Information Processing (ICIIP), 2017.

[14] Anon. Institute of Medical Biometry, Informatics and Epidemiology of the MedizinischeEinrichtungen der Universität Bonn. 2017. http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3

[15] M. Zeng, C.yu Zhao ,Q.Hao Meng,” Detecting Seizures From EEG Signals Using the Entropy of Visibility Heights of Hierarchical Neighbors”, IEEE Access , vol. 7,pp 7889-7896, 2019.