State Transfer Network of Time Series Based on Visibility Graph Analysis for Classifying and Prediction of Epilepsy Seizures

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***Abstract*— Visibility graph analysis of time series became widely used as a time series analysis in the recent years. State transfer network is a network of mapping mono/multivariate time series into a network of local states based on visibility graph, it was used to study the evolutionary behavior of time series and in this study, we applied this principle to the detection of epileptic seizures. Two sets of EEG data were used; first set was obtained from subjects with the healthy brain and the second set obtained from an unhealthy part of the brain during existence of epileptic seizures. Results show a clear discrepancy between the two groups of data with a dominantly appearance of particular nodes in the networks of an epileptic group called hubs or motif, accordingly, the visibility graph network analysis based analysis can be considered as a prediction way of epilepsy seizures.**

Keywords — visibility graph, time series, network, node, epilepsy, seizures.

I. INTRODUCTION

Electroencephalography (EEG) is a very detailed electrical signal containing information about the brain, where it produced by complicatedly interaction between a huge number of neurons [1]. Epilepsy is a neurological disease or disorder afflicting over 50 million individuals worldwide [2], its characterized by a state of functional disconnections in form of abnormal seizures within neuronal population [3]. Seizures occur in response to firing activity and hyper-excitation of some neurons in synchronous form. [4] [5] [6].

Several researchers have put a lot of effort in providing methods to distinguish and classify the normal and abnormal brain states by help of analyzing EEG of Epilepsy data. Where part of these methods is based on linear analysis principle, most of other methods rely on the nonlinear analysis. For example: linear univariate features of statistical moments [5], spectral power and mutual information of time series [7][5], frequency and wavelet analysis [8] have used in some linear classification techniques and Lyaponuv exponent, correlation dimension, approximate entropy and Hurst exponent [1], phase synchronization and synchronization likelihood [9], are some of nonlinear techniques. Nonlinear analysis of time series data such as EEG has showed their advantages over the linear methods in extracting valuable features and classification of high complexity of such multivariate data [10]. Recently, the geometrical network analysis of time series as a nonlinear tool became highly importance because it bring the ability to study multivariate time series data into both macrospace and microspace dimension [11], [12].

The Visibility Graph analysis of multi-channel EEG is a new nonlinear tool intended to map the time series signal into a graphical form according to its geometrics visibility characteristics [13-15], and producing a network of local stats, which can investigate visually the structural patterns at different time scales from microscopic to macroscopic levels. This technique helps in capturing precise information of time series states and able to analysis non-stationary time series [16].

The goal of this study is to classify and distinguish between two EEG data types: one from unhealthy brain with epileptic seizures and the other data from subjects with healthy brain, and provide a conclusion might help on future prediction of epileptic seizures.

II. MATERIALS AND METHODS

A. Data

The experimental data that used in this study was selected from PhysioNet Database from Epilepsy center, Bohn University, Germany. The data includes five sets of EEG recording, two sets A and B was recorded from 5 healthy subjects with opened and closed eyes by placing electrodes on the outer surface of the skull (set A), and prior to seizure two sets were recorded from part of the brain with epilepsy syndrome (C) and from the healthy part of the brain (opposite part, D), and the fifth set were recorded during the epilepsy seizure (E). Each set includes 100 data sample recorded from different channels. During this study only sets A and E were used during this study. More details about data recording conditions can be found in reference [10]. Fig. 1 shows exemplary samples of the selected data.

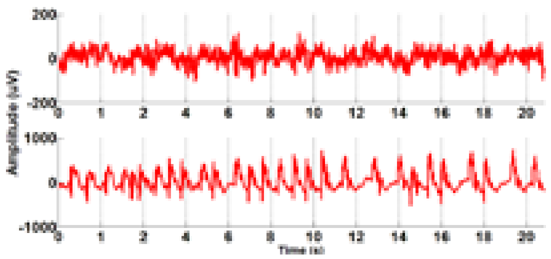

Figure 1. Two different samples of recorded EEG signals; Top refers to healthy data, bottom refers to epileptic seizures unhealthy brain.

B. *Visibility Graph*

The visibility graph is a tool to extract structural information embedded in the segments and describe the local states in different time duration [16]. This network can inherit several properties of the time series [11].

A window with size s slide along a time series, {y1,y2,...,yN}. The covered segments read as follows:

$$Y_k = \{y_k, y_{k+1}, \dots, y_{k+s-1}\}$$
$$k = 1,2,\dots, N-s+1$$

The segment Yk is mapped to a visibility graph, each data value is considered to be a node. Two nodes are connected if they can see each other, namely, a straight visibility line exists between them. Formally, two arbitrary data values y_a and $y_b$are visible to each other if each point $y_c$between them satisfies the criterion:

$$y_c \le y_b + (y_a - y_b).\frac{b-c}{b-a} \qquad (1)$$

where a, b and c are the index of each data value y_a, y_b and y_c respectively. The constructed visibility graph can be represented with an adjacency matrix g_k, whose element $g_k(a,b)$ equals $1(0)$ if y_a and y_b are visible (invisible). This results into an s by s matrix for the k^{th}segment.

By sliding the window over the whole time series, a set of adjacency matrices $G = \{g_1, g_2, \dots, g_{N-s+1}\}$ is obtained corresponding to $N - s + 1$ segment.

State transfer network

A distinguishable locale states considered as having a unique adjacency matrix $g_k$and a directional transfer-link connecting two states ($g_a$and g_b) means that both sates are occurred immediately after each other. Consequently, state chain with directional links is obtained in this form:

$$g_1 \to g_2 \to \cdots \to g_{N-s+1} \qquad (2)$$

The unique local states defined to be nodes and the number of links between two pair of nodes is the weight of link. This mapping procedure of time series into distinguishable connected states by mean of visibility graphs is called transfer network with edge direction refers to the link direction and transfer times refer to the edge weight.

Hubs and Motifs

If the degree (occurring frequency) of one node is significantly large compared to other nodes, the node is called hub. The mapping process may be repeated for shuffled versions of original time series, then if the node degree in the original time series is significantly larger than in the shuffled one, the node is called motif. The significantly large links between hubs and motif could inherent helpful information about time series characteristics and short-term and long-term prediction.

Window size

According to [16], the window size selection is important and key problem; it should be large enough to distinguish different states and small enough to be sure the state transfer network and the subsequent structural characteristics are statistically significant. And for deterministic time series the minimum embedding dimension can be useful or if there exists a natural period or interval of interest, this period can be selected as windows size.

The node positions, degrees and link weight of transfer network were computed by MATLAB 2013b®, and in Fig. 2 main blocks of computation process are illustrated.

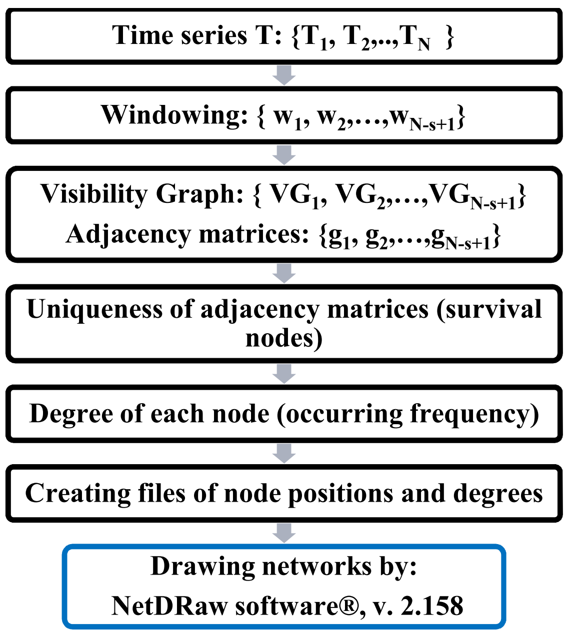

Figure 2. Block diagram illustrating the computation steps of state transfer network.

III. RESULTS

In our study the window size was selected to be 10 for two reasons: first, some previous studies for phase space construction of similar EEG data suggested that minimum embedding dimension to be in range 5 to 10 [17]; second, when the window size increased above 10 the link degrees between states converge to be unity which in turn couldn't provide useful analysis about time series behavior.

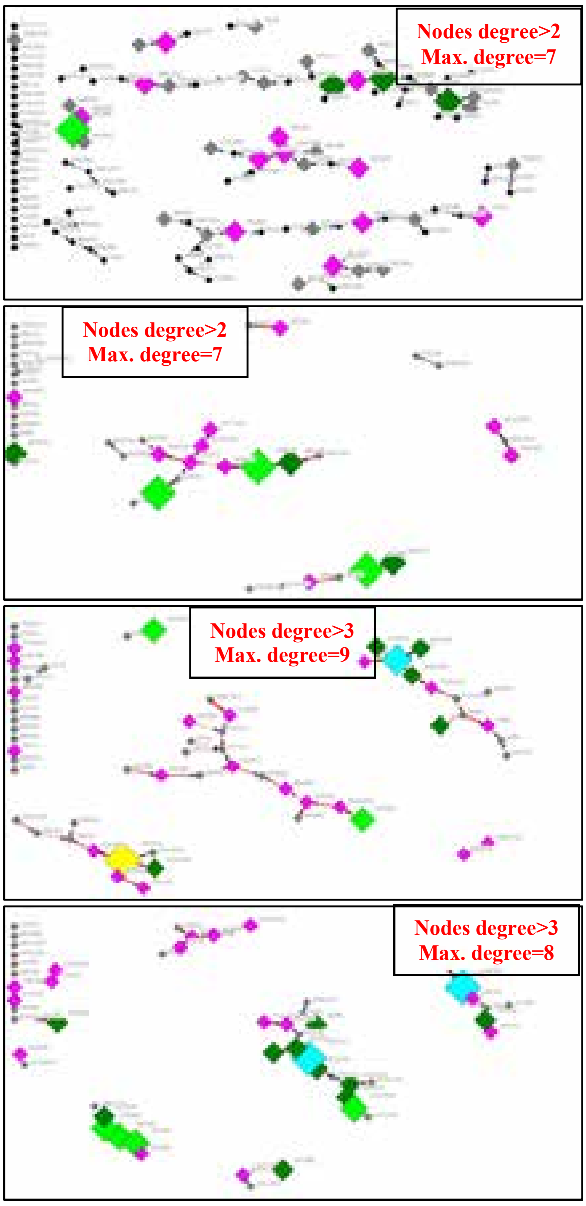

Figure 3. State transfer networks of four times series from set A, different colors refer to the different in node degree. Line width refres to the connection strength between two node-pair. For each network the filtered out degrees and maximum node degree are indicated in top-box.

Accordingly, the state transfer network of ten segments from each data set A and E with 4097 number of samples for each segment and window size $s = 10$ can be displayed as in Fig 3 and Fig 4 respectively (only four networks of each set is displayed to fit with the number of allowed pages of the conference).
The nodes of low degrees are filtered out in order to show a clear network, filtered degrees are displayed in the top of each figure, and furthermore, the boxplot of maximum occurrence degree for 10 segments of each data set is calculated as shown in Fig.5.

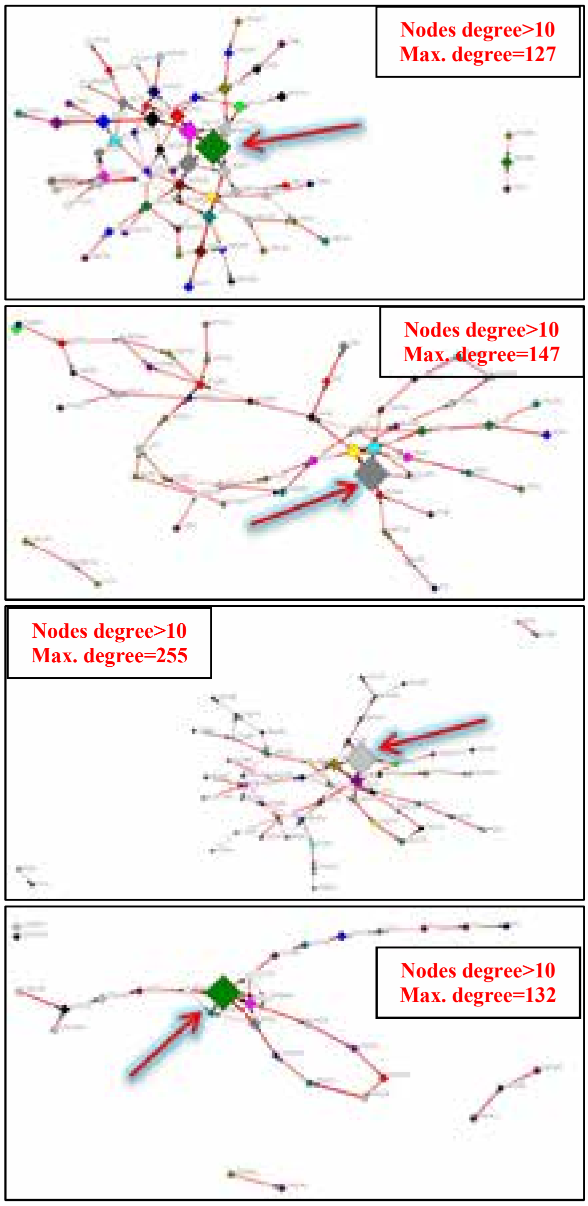

Figure 4. State transfer networks of four times series from set E.

It's obviously clear the topological difference between the state transfer networks of set A and E; for set A, one can see more flatness of networks and less amount of connection for each node while in set E the connection amount is significantly large and networks shows the tendency to be in group-shaped like, moreover, the number of sub disconnected networks is larger in set A than in set E. But the most important noticed result here is the appearance of almost one dominant hub (motif) in the networks of set E (as indicated by red arrow in Fig4) with significantly large degree and more than one hub can be observed for networks of set A (as its indicated by nodes with the same color in Fig 3).

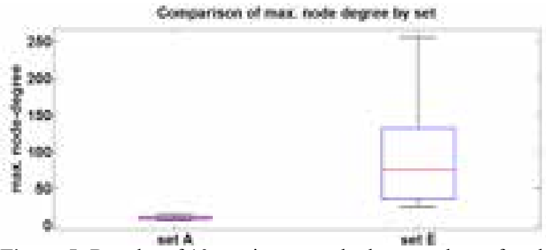

Figure 5. Boxplot of 10 maximum node-degree values of to data sets A and E.

IV. CONCLUSION

The results in this study reflect a tendency for set E's networks to be represented by dominant hubs (motifs) and high connectivity rate between local states (node-pairs) rather than to includes non-dominant multiple of similar hubs (motifs) as in set A's network. By returning back to the brain activity during epileptic seizures epoch and during normal seizures epoch; one can say that as the epilepsy cause a discharge of nerve tissues in all degree ,the brain becomes globally activated in the abnormal-state unlike spatially active in the normal-state [18], accordingly, one conclusion can be stated as the more the brain activity spatially extended during epileptic seizures the more the connectivity rate between node-pairs to be happened and more tendency for hubs (motifs) to appear dominantly. This conclusion lead to another conclusion of start of existence of dominant hubs (motifs) can be consider as a prediction way to seizure occurring.

This method comes in a good agreement with some previous studies of seizures onset prediction such as global filed synchronization [4], decrease in synchronization between certain recording sites [19].

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