Synchronization Analysis of EEG Epilepsy by Visibility Network Graph and Cross-correlation

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***Abstract*— Epilepsy is a chronic neurological disorder affects people of all ages; this paper presents cross-correlation and state transfer network method to analyze synchronization between EEG data-channels from subjects with epilepsy seizures. The datasets are in two phases, preictal and ictal phase. All EEG segments are mapped into a corresponding state network graph to obtain the corresponding motifs and then the cross-correlation is applied to exhibit the synchronization changing during epilepsy seizures. The results showed that ictal phase presented high synchronization between channels, where low synchronization level is observed within preictal phase.**

Keywords — Epilepsy; Visibility Graph; Synchronization.

I. Introduction

Epilepsy is one of the most common and devastating neurologic diseases, afflicting over 50 million individuals worldwide [1], epileptic seizures occur as a results of firing activity of some synchronously neurons, and when this synchronized arrangement disturbed and becomes abnormal the epilepsy takes place [2]. Such seizures can be found mainly in form of three phases: ictal phase occurs during a seizure time, interictal phase take place between seizures and postictal phase occurs after a seizure [3].

Different factors like shape, size and functional connectivity of brain make it a complex and chaos system [4], that exhibits inability to predict future response of such a complex system. Such chaotic behavior of brain could be responsible for epilepsy and other disorders, especially at neural level [5]. Epilepsy recordings have high advantage over other recordings due to its unique view of the dynamical system human brain. The sudden and unpredictable occurring of the epilepsy seizures still as one of the major disabling aspects that needs a strong tool to be overcome and makes epileptic seizers predication clinically useful [6]. Consequently, many linear and nonlinear analysis methods have been used for understanding such coupled behaviors in the human brain. Several recent studies have been applied on the characterization of epileptic brain states and proofed that nonlinear EEG analysis of recorded seizures is of primary importance in providing strong evidence that the seizures states are not an abrupt or fully random phenomenon [2],[7], [8]. Numerous seizure prediction algorithms for nonlinear EEG analysis were proposed among using correlation integral, correlation dimension, Lyapunov exponent, entropy measure of phase clustering and generalized synchronization [5], [1], [9], [10]. The generalized synchronization becomes recently very important nonlinear statistical tool that reflects general relationships between states of two systems, such that a dynamical state of one system is completely determined by the state of the other system. The synchronization distribution between different parts of the brain is of primary importance which is leading to another useful way of understanding the nervous system diseases [11].

The aim of this study is to apply the visibility graph (VG) as a nonlinear analysis method on electroencephalograph data from different brain region and different pathological states (for healthy subjected and epilepsy patients), Then the obtained VG nodes are transformed to network states by State transfer network (STN) method. This method was applied on experimental data contains two sets of EEG recording: preictal and ictal datasets refer to EEG-recording phase before epileptic seizure and during epileptic seizure respectively. To the best of our knowledge, this is the first study of applying STN and cross-correlation on epilepsy data.

II. Materials and Methods

A. Data

EEG data obtained from 10 subjects who were diagnosed with epilepsy in Izmir Katip Celebi University, Faculty of Medicine, Department of Neurology, Turkey. The data comes in three sets or phases: preictal, ictal and postictal phase. The records were obtained using 18 electrode-channels placed on the skull following 10/20 system. The EEG signals were digitized at 100 samples/sec (Hertz) sampling rate with a 12 bit analog to digital converter, and then the data is digitally filtered using (1–50) Hz. band-pass filter. Some recorded data contained motion artifacts, as such we selected the most suitable records after visually inspecting and omitting the undesired segments. Figure 1 shows one example of used datasets in this study.

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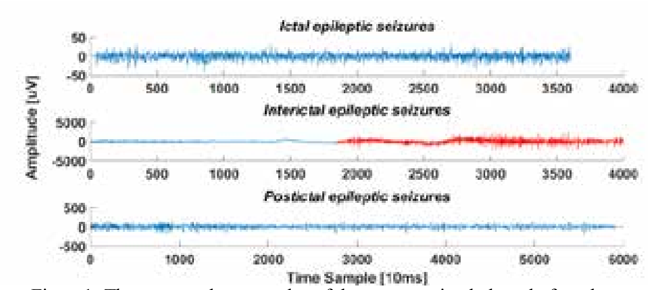

Figure1: Three exemplary samples of data sets: preictal phase before the epileptic seizure to start (top), ictal zone which appeared between preictal and postictal phases (middle, >2000ms) and postictal phase when the interictal zone disappeared (bottom).

B. EEG decomposition

A wavelet transform is a mathematical tool for decomposing signals into multiple sub-signals which have many applications in EEG data analysis. In this work, the wavelet analysis was used to decompose the recorded EEG data into five frequency bands (Δ, Θ, α, β, γ). Daubechies 4 (db4) mother wavelet was selected to decompose the EEG data into five levels to obtain the particular frequency bands [14], Analysis of decomposition was done by MATLAB 2013b®. Table 1 shows the frequencies range for each decomposed band:

TABLE I. FREQUENCY BANDS CORRESPONDING TO DIFFERENT DECOMPOSITION LEVELS.

Decomposed Signals	Frequency bands (Hz)	Decomposition level
D1	43.4-86.8	1 (noises)
D2	21.7-43.4	2 (gamma)
D3	10.8-21.7	3 (beta)
D4	5.40-10.8	4 (alpha)
D5	2.70-5.40	5 (theta)
A5	0.00-2.70	6 (delta)

The 5 decomposed levels and the full band are used as the input data for VGS method and for each data set there are six data bands with 100 samples for each one. The analysis includes calculating of VGS for each particular data set-band pair of 100 channels.

Constructing Visibility Graph (VG).

In time series x consider a_i as the i^{th}node of the graph that corresponds to the i^{th} point of the time series, x_i. A unidirectional edge is existed between two nodes of the graph, a_m and a_n, if and only if:

$$\frac{x_{c_j} - x_n}{n - c_j} < \frac{x_m - x_n}{n - m}$$

$$\forall_j \in Z^+; j < n - m. \qquad (1)$$

This means that the difference between the first target point (x_n) and the second target point (x_m) with respect to their inter-distance on the time series ($n - c_j$) must be greater than the same difference ratio between (x_n) and all other intermediate points (x_{c_j})'s .Figure 2 explained the procedure of converting time series x (Figure 2 (upper part) to its VG Figure 2 (lower part)). Each x_j in the time seris is represented by one corresponding node a_i , and the gray lines connecting two time points x_i and x_j if and only if the two corresponding points are visible to each other (*i.e if all points between x_i and x_j have amplitude value less than amplitude of x_i and x_j*), therefore, the corresponding nodes of the VG a_i and a_j are connected by bidirectional edge.

C. State transfer network

The time series is subdivided into small windows with size *s* and VG of each window is computed in form of adjacency matrix; in the adjacency matrix each point has a value 1 (0) which mean that the two points within the window are connected (not connected). 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:

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

Where *s* is the window size. The unique local states defined to be nodes and the number of links between two pair of nodes is the weight of link. This procedure of mapping 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.

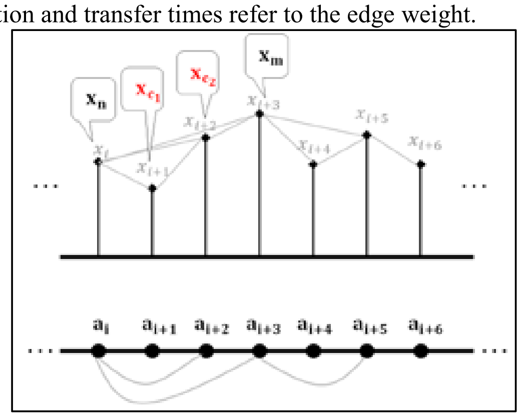

Figure2: Illustration of a time series (upper part) converted into its VG (bottom part). Each point in the time series is represented as x_n , and the second check-connection point as x_m, and the intermediate points as x_{c_j}.

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 (s)

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®. Figure 3 illustrate the main blocks of computation process of STN method.

D. Cross correlation

The cross-correlation between two time series x_t and y_t is given as in following formula:

$$\sigma_{xy}(T) = \frac{1}{N-1}\sum_{i=1}^{N}(x_{t-T} - \mu_x)(y_t - \mu_y) \qquad (3)$$

where μ_x and μ_y are the means of each time series and there are N samples in each.

We took one single subject-EEG data which contains 18 channels and applied it to wavelet decomposition and STN to extracting their corresponding motifs, then we choose one single motif (motif 1 for example) of one single data band gamma for example) from one single dataset (ictal set for example). Afterward, we plotted the EEG data channels and the motif series on the same graph, (here the motif series is the motif-node occurring positions in the original time series).

Time series: $x_t=\{x_1, x_2,..,x_N\}$

Windowing: $\{w_1, w_2,\dots,w_{N-s+1}\}$
where $w_i=\{x_n,x_{n+1},\dots,x_s\}$ is one subset of length s from the original time series x_t

Visibility Graph: $\{VG_1, VG_2,\dots,VG_{N-s+1}\}$
constructing VG of each window w_i

Adjacency matrices: $\{g_1, g_2,\dots,g_{N-s+1}\}$

Uniqueness: reducing the number of adjMatrices bu removing repeated adjMatrix (survival nodes)

Degree of each node: occurring frequency of each surviing adjMatrix, **motifs** and **hubs** created in this stage by extractin the most occured node (adjMatrix repetetion)

Figure 3. Block diagram illustrating the computation steps of state transfer network.

(*The reason why we only choose one single results is the big amount of possible results that can't be display sufficiently in limited paper area and at the same time, the single displayed results is enough to explain the idea.* Figure 4.

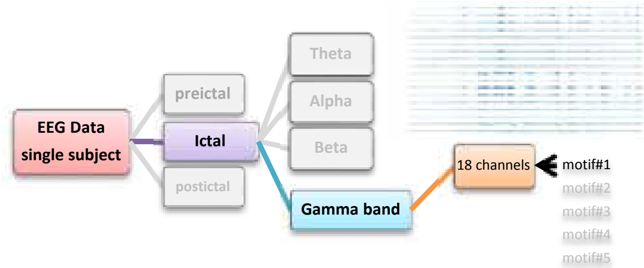

Figure 4: one single dataset (interictal) from one subject was selected, and 18 channels of its gamma band were plotted.

III. RESULTS

We displayed our results in the following manner: first, the time series of all channel data are displayed, then the selected motif series is displayed over the channel series as index-marked position, then for one selected channel the each corresponding window-segment of motif series is displayed, after that the cross-correlation between the selected segments of each channel is displayed with the mean of all of them as well. Figure 5 below shows the motif series for 18 channel of gamma band from ictal dataset, the occurring position of one single motif (motif#1) were marked as "+" and displayed on the original time signal (i.e. on one extracted gamma band signal), here we zoomed ch18 plot to display the motif series over the time signal more clearly.

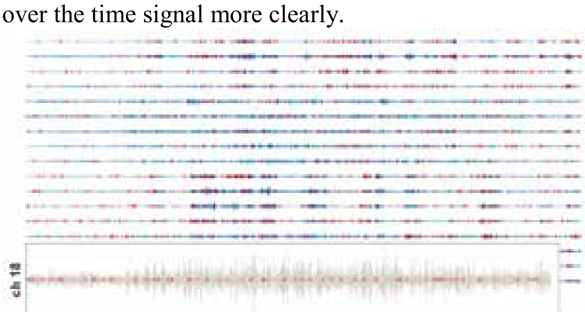

Figure 5: plot of 18 gamma-channel (blue line) and the motif#1 series of each one ("+"), ch18 zoomed and shows more clear view.

The motif series means that the same node (node is one motif) is repeating itself at different position over original signal, and the node refers to one window of time samples from the original time signal, so if we take only ch18 from gamma time-signals and plotting all possible time-window samples of its corresponding motif, we get a plots like in figure 6, (Note that the window size is 10, and number of all possible time-window samples is equal to the length of motif#1 series.)

Here, length of motif#1 series is 79 for ch18, this mean that 79 window-time samples should be exist in the original time-signal (ch18) corresponding to these 79 positions and these samples should be similar to each other by assumption. In order to evaluate that, we used averaged cross-correlation between all window-time samples to check their similarities, then we applied the same process for all other channels and calculated the averaged of averaged cross-correlation over all channels. The results showed high correlation between all samples of each single channel and between all channels, these averaged cross-correlations of 18 channels are displayed in figure 7 followed by their overall average.

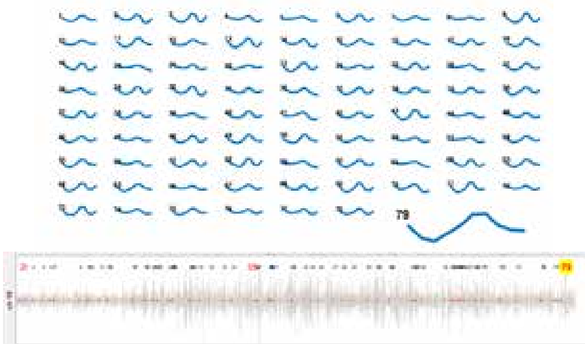

Figure 6. The corresponding window-time series of motif#1 of ch18 signal, the motif#1 include 79 occurring positions over ch18 signals, each position is linked and indexed by a number refers to one window-time sample, at position 79 the window sample was zoomed up, the bottom figure shows both time signal and motif series with index numbers.

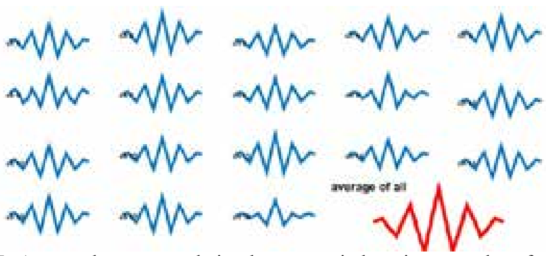

Figure 7: Averaged cross-correlation between window-time samples of each individual channel (index number refers to the channel number). The average of all these averaged cross-correlations is displayed at the right-bottom side.

We repeated the same procedure for Gamma band of preictal dataset and the result mean of cross-correlation between all 18 channels is displayed in figure 8.

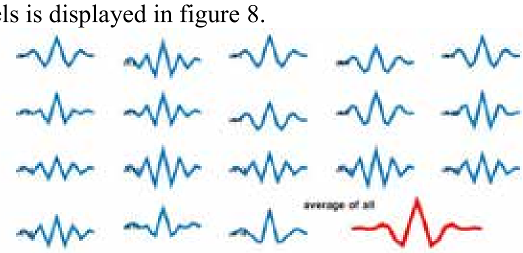

Figure 8: Averaged cross-correlation between window-time samples of each individual channel for preictal dataset (gamma band).

The mean cross-correlation of both datasets is displayed in one scale as in figure 9, it is cleared from the figure that ictal phases exhibit higher correlation between its motif-patterns than preictal phase which support the assumptions of increasing synchronization within epileptic regions.

IV. CONCLUSION

In this study the analysis of two epileptic datasets by STN is used to study the synchronization behavior during epilepsy seizures. The obtained motifs from 18 channels are used to specify the occurring position of similar patterns among each data series. The average of cross-correlation between these patterns are obtained and showed a clear difference between the datasets (the gamma band from each dataset).

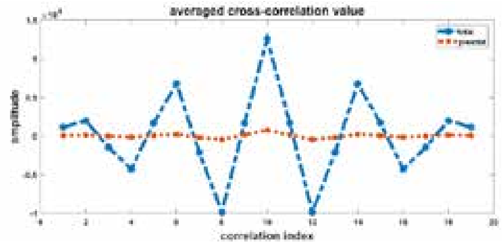

Figure 9: The average of cross-correlation of motif-based patterns between all channels for preictal (red) and ictal dataset (gamma-band data).

These results leads to a conclusion of increasing the synchronization between data channels during the epilepsy seizures and absence or less appearance of such synchronization during the phase before seizures to start, accordingly, the STN method can be considered as an effective tool for analyzing epilepsy EEG data.

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