Synchronization Analysis of EEG Epilepsy by Visibility Graph Similarity

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***Abstract*— Epilepsy is a neurological disorder of different types characterized by recurrent of seizures which affects people of all ages. This paper presents visibility graph similarity as a nonlinear model to analyze the epilepsy EEG data from different brain region of healthy and patient subjects with epilepsy seizures. All EEG segments are mapped into a corresponding graph to obtain the corresponding degree of sequence for each segment, and then the difference between these degrees is constructed as a similarity between two segments. The results showed that seizure activity presented strongest nonlinear dynamic response in the form of similarity level decreasing from healthy subjects to patients. Results of other sets were found to be in agreement with our results.**

Keywords — Epilepsy; Seizures; 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].

Recently, the brain dynamical behavior or complexity due to its shape, size and functional activity is considered as highly nonlinear chaos system [4], which is simply referred to the inability to predict future response of such a complex system. Such chaotic behavior of brain could be responsible for epilepsy, schizophrenia, insomnia and other disorders, especially at neural level [5], [6]. Epilepsy recordings have highly advantage over other recordings due to its unique view of the dynamical system in the 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 [7]. 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], [8], [9]. Numerous seizure prediction algorithms for nonlinear EEG analysis were proposed such as correlation integral, correlation dimension, Lyaponuv exponent, entropy measure of phase clustering and generalized synchronization [5], [1], [10], [11]. 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 disorders [12].

The aim of this study is to apply the visibility graph similarity (VGS) as a nonlinear analysis method on electroencephalograph data from different brain region and different pathological states (for healthy subjected and epilepsy patients). This method was applied on a publicly available data contains three sets of EEG recording: A and B sets refers to opened and closed eyes recording from 5 healthy subjects respectively, and E set was recorded from 5 patients during the epilepsy seizures [13]. To the best of our knowledge, this is the first study of applying VGS on epilepsy data.

II. Materials and Methods

A. Data

The selected data in this study are obtained from the Epilepsy center in Bonn, Germany by [13]. The data includes five sets. Two sets were recorded from 5 healthy subjects with either opened or closed eyes (A and B). Two sets were recorded prior to seizure from a region of the brain with epileptic focus (C) and from the healthy part of the brain (opposite part, D). The fifth set was recorded during the epilepsy seizure (E). Only sets A, C and E were used during this study. Each set contains 100 single channel, all EEG signals were recorded at a sampling rate of 173.61Hz for 23.6-sec duration and 128-channel amplifier system was used with band-pass filter settings were 0.53–40 Hz (12 dB/oct) and 12-bit analog-to-

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digital conversion. Figure 1 shows five different EEG samples belongs to set A, B, C, E and D from top to bottom.

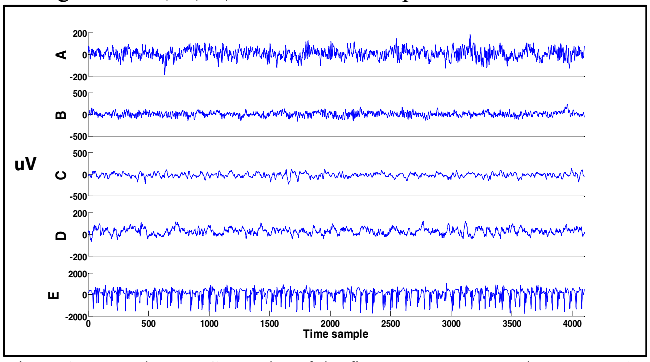

Figure 1: Exemplary EEG samples of the five sets. From top to bottom: set A to set E (denoted EEG-A to EEG-E). Amplitudes of surface EEG recordings are typically in the order of some µV. For intracranial EEG recordings, the amplitudes range is around some 100 µV. For seizure activity, these voltages can exceed 1000 µV.

B. Data analysis

EEG decomposition

A wavelet transform is a 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.

C. Visibility Graph Similarity

Visibility graph similarity is a neural network method developed to predict the generalized synchronization in term of similarity, it's a new tool intended to map the time series signal into a graphical form according to its geometrics visibility characteristics and estimating the average similarity between the corresponding patterns [15], [16]. In a visibility graph, each two nodes represent two different time samples, where if two-time samples can see each other, then their corresponding nodes connected by one edge. VGS based methods more robust than normal coherence and synchronization likelihood methods for assessing the similarity between two-time series.

The following steps explain the VGS algorithm as shown in Figure 2:

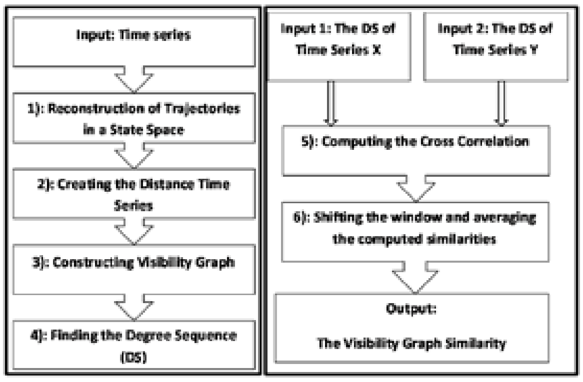

Figure 2: six steps for computing Visibility Graph Similarity; right block represents the stages of extracting the Degree Sequence (DS) of each time series and block B demonstrates how similarity between the DSs of two series is computed.

1. Reconstruction of trajectories.

According to chaos theory, there are two main parameters for reconstruction state space trajectories of time series, embedding dimension (m) and lag time (L) [17]. The state space representation of such trajectory is represented as follows:

$$X_{k,n} = [X_{k,n} \quad X_{k,n+L} \quad X_{k,n+2L} \quad \dots \quad X_{k,n+(m-1)L}] \qquad (1)$$

where $X_{k,n}$is the n^{th} element of the k^{th} time series $(k = 1, 2, \dots, M;$ M different systems are coupled together). As a result, each trajectory includes number of states less than the time series samples by one state length$(m - 1)L$. The embedding dimension and time delay must be determined carefully to avoid loss of information within the reconstructed trajectories.

2. Creating the Distance Time Series (DTS).

A reference state $X_{k,n}$ is defined as the middle of window of length $2(w2)$, where $w2$ is an integer number referring to the maximum state distance from the reference state. This window contains two sets of states $X_{k,m}$ of width of $2(w2 - w1)$ before and after the reference state, such that the first set start from distance of w2 till w1 before the reference state and the second set start from distance of a w1 (w1 is the Theiler correction) till w2 after the reference state: $[X_{k,n-w2} \quad X_{k,n-w1}]$ and $[X_{k,n+w1} \quad X_{k,n+w2}]$. The Euclidian distance between the reference state and the selected window of states is constructed in form of time series.

3. 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 exist between two nodes of the graph, a_m and a_n, if and only if:

$$x_{m+j} < x_n + \left(\frac{n-(m+j)}{n-m}\right)(x_m - x_n) \qquad \forall_j \in Z^+; j < n-m. \qquad (2)$$

Figure 3 explained the procedure of converting time series x (Figure 3 (upper part) to its VG Figure 3 (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, therefore, the corresponding nodes of the VG a_i and a_j are connected by bidirectional edge.

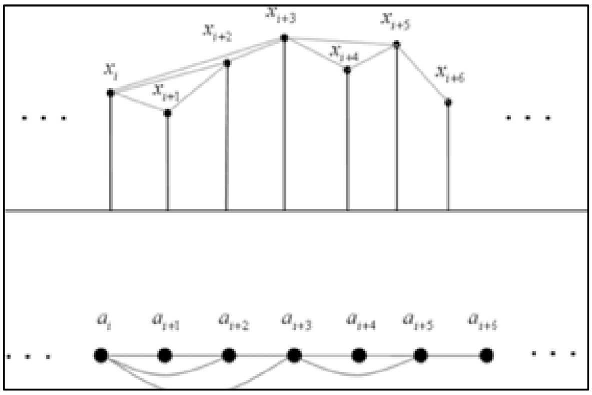

Figure 3: Illustration of a time series (upper part) converted into its VG (bottom part).

4. Computing the Degree Sequence (DS).

A number of connected edges to one node determine the degree of that node. The whole series of these degrees for a set of nodes called degree sequence and it is obtaining for each DTs.

5. Finding the cross correlation between the DSs.

In the proposed VGS, The similarity between the constructed DSs within one window of trajectories is obtained by computing the cross-correlation function which reflects the dynamic similarity of the coupled system:

$$S[DS(X1), DS(X2)] = \left|\frac{COV[DS(X1), DS(X2)]}{\sigma_{DS(X1)}\sigma_{DS(X2)}}\right| \qquad (3)$$

where $DS(X1)$ is Degree Sequence of the trajectory X1 within window $(w1, w2)$, $|.|$ the absolute value, $\sigma(X1)$ is the standard deviation of X1, and $cov[X1, X2]$ is the covariance of X1 and X2.

6. Averaging cross-correlation overall shifting the windows.

The selected window is moved with small steps of shifting overall the time series. The width of the window is 410 the same as suggested by [11]. Then to obtain the VGS, the overall synchronization of M time series is obtained by averaging the computed synchronizations over all shifted windows.

III. RESULTS

In this study, the VGS was applied as a powerful nonlinear tool on EEG recorded data from different brain region with different pathological states. The VGS was used to predict the inherent similarity between spatiotemporal sets of EEG data based on their complexity deteriorating during epileptic seizures.

The average visibility graph similarities were constructed from three sets of EEG time series (A, B and E) and their corresponding six frequency bands. The constructed average VGS were plotted versus the six different bands for each selected EEG sets as shown in Figure 4.

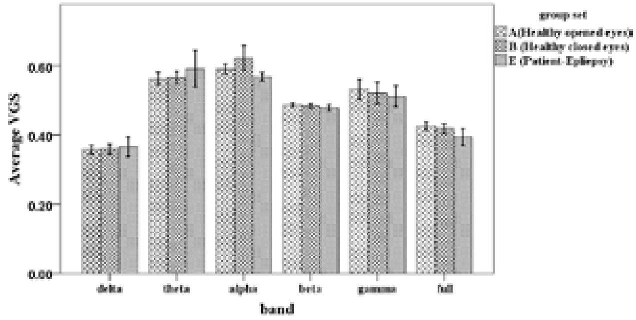

Figure 4: The Average Visibility Graph Similarity for six deferent bands and three groups A, B and E. Error bars displayed as standard deviation difference for each individual band.

For each frequency band, the data was analyzed by two-way repeated measures ANOVA (ANOVA analysis was computed by IBM SPSS Version 20.0®). In two-way ANOVA, the two factors were set as the group type with 3 levels A, B, and E, and the frequency band with 6 levels (Δ, ϴ, α, β, γ and full band), The dependent variable is the 100 mean value of VGS for each band*group index. From the results of ANOVA for each of the frequency band, it's shown that there was a significant effect in the interaction between group and band factors, table 2 shows ANOVA analysis results.

TABLE II. TWO-WAY REPEATED MEASURES ANOVA OF OBTAINED VGS FOR 3 GROUPS A, B AND E, AND SIX BANDS (Δ,ϴ,Α,Β,Γ AND FULL BAND). THE AVERAGE VGS CONSIDERED AS THE DEPENDENT VALUE OF 100 POSSIBLE VALUES FOR EACH BAND_GROUP COMBINATION.

Source	Type III Sum of Squares	Mean Square	Sig. *p-value*
GROUP	0.020	0.020	0.000
BAND	0.000	0.000	0.229
GROUP * BAND	0.082	0.082	0.000

Figure 5 shows the full-band average along 100 channels. A clear result shows a dominant in high VGS for set A and B rather than set E, where average VGS is 0.4266, 0.4185 and 0.3936 for group A, B and E respectively.

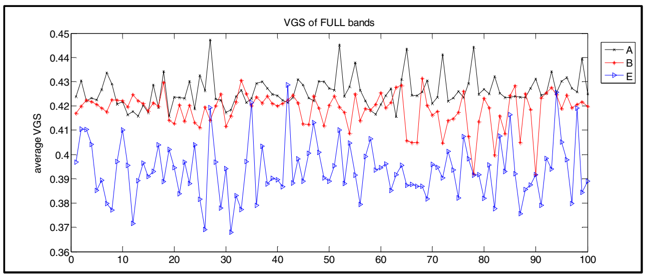

Figure 5: The Average VGS in the full band for 100 channels and each of the three groups A, B, and E.

IV. CONCLUSION

This study shows that VGS is an effective and useful nonlinear tool to distinguish between multichannel EEG recordings from healthy control and non-control patient with epilepsy disorder.

A significant difference in similarity between two EEG-data sets; healthy controlled subjects (set A and B) and non-controlled subject with epileptic seizures (intracranial recording, set E) is shown as in Figure 4. The significant decrease in similarity can be noticed in higher frequency bands (alpha band, gamma band and the full band) between the main two sets of subjects (healthy control and non-control subjects). For delta, theta and beta bands the value of VGS are almost the same for closed and opened eyes. This loss in synchronization that presented by VGS results may be due to the hypothesis that states the stimulation of different region during the seizers happening at different time points, which leads to non-synchronization or dissimilarity patterns [2], [17]. Consequently, These results are in line with a previous study using PSVG (Power of Scale-freeness of Visibility) [21] were showed a decreasing in the similarity between same EEG sets of healthy epileptogenic subjects, and agree with previous research that showed a decrease in similarity (synchronization) [2]. Also these results come in an agreement with similar analysis applied on different neurologic diseases such as global field synchronization (GFS) and global synchronization index in Alzheimer's disease [18, 19].

To our knowledge, this is the first study of applying VGS on such epilepsy data. Moreover, VGS provide more accurate measure of the overall synchronization than other generalized synchronization prediction methods like SL, also it has the ability to detect the temporal synchronization sooner than SL with less amount of required parameters [20] which may lead to consider it as evaluation tool to study epilepsy data.

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