Automated Detection of Epilepsy by Improved Recurrence Parameter

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Abstract: We present different methods like order recurrence plot and mean conditional probability of recurrence and other measures to visualize behaviour of two dynamical system using recurrence quantification analysis for measurement of coupling strength with robustness against noise, non-linear distortion and low frequency trend. This has application for the identification of boundaries of the onset and loss of coupling in between identical and non- identical biomedical signals. Comparison of these methods i.e. order recurrence plot and mean conditional probability of recurrence is performed with other techniques in detection of the direction of the coupling in weakly as well as strongly coupled systems.

Keywords: CRP, EEG, Recurrence Rate, RQA.

1. Introduction:

Recurrence is a fundamental characteristic of many dynamical systems. This recurrence property is exploited to characterise the system's behaviour in phase space. The concept of recurrence is used for the analysis of data and to study dynamical systems. It is a powerful tool for the visualisation of dynamical systems and analysis which was introduced by Poincare in 1890 [1]. Thus recurrences contain all relevant information about the system's behaviour. The method of Recurrence Plots (RPs) is extended to the CRPs. The method of CRPs enables us the study of synchronization or time differences between two different time series and this is emphasized in a distorted main diagonal in the CRP called the LOS. Thus, first we introduce the definition of Recurrence plot and Cross Recurrence plot and then LOS and its applications to the biomedical signals. Complexity measures based on CRPs are introduced in the thesis and their applications to biomedical signals is studied. In this manner we are able to distinguish biomedical signals based on the CRP plots and complexity measures values. Next, synchronization analysis is also done on driven oscillators and it is used to know whether the oscillators are in Phase Synchronization (PS) or in non-Phase Synchronization (non-PS). The application of the PS is done on biomedical signals and how the biomedical signals can be distinguished based on PS is studied. Synchronization analysis also includes Generalized Synchronization (GS) based on recurrences and its application to driven oscillators and biomedical signals is observed.

Cross Recurrence plots enables us for the study of synchronization or time differences between the given two time series. This is emphasized in a distorted main diagonal in the cross recurrence plot called the LOS. From the method of CRPs, we have found an interesting feature of it. Besides the possibility of the application of the recurrence quantification analysis [2], there is a more fundamental relation between the structures in the CRP and the considered systems. Finally, this feature can be used for the task of the synchronization of data sets. Before any time series analysis can be started, the data series have to be synchronized to the same time scale. Usually, this is done by comparing and correlating both the data sets. Some techniques for this kind of correlation and adjustment have been suggested [5].

The recurrence plot exhibits characteristic patterns for typical dynamical behaviour [1,6]. A collection of single recurrence points, homogeneously and irregularly distributed over the whole plot, reveals a stochastic process. Longer, parallel diagonals formed by recurrence points and with the same distance between the diagonals are caused by periodic processes. A paling of the RP away from the main diagonal to the corners reveals a drift in the amplitude of the system. Vertical and horizontal white bands in the RP result from states which occur rarely or represent extreme states. Extended horizontal and vertical black lines or areas occur if a state does not change for some time, e.g. laminar states. All these structures were formed by using the property of recurrence of states. It is said that the states are only the "same" and recurrence is determined by the distance ε.

2. Related Work:

The study of coupled systems goes back to the 17th century and begins with the analysis of synchronization of nonlinear periodic systems. Well known examples are the synchronization of two pendulum clocks that hang on the same beam (it was through this system, that Huygens discovered synchronization), the synchronized flashing of fireflies, or the peculiarities of adjacent organ pipes which can almost annihilate each other or speak in unison. But the research of chaotic synchronization does not begin until the eighties where it was shown that two chaotic systems can become completely coupled, i. e. their time evolution becomes identical. This finding has had very important consequences for the design of secure communication devices. The synchronized chaotic trajectories can be used to mask messages and prevent their interception. In the notion of complete synchronization of chaotic systems was generalized, allowing the non identity between the coupled systems. And some time later, Rosenblum et al. [1] considered a rather weak degree of synchronization between chaotic oscillators, of which their associated phases become locked, whereas their amplitudes remain almost uncorrelated. Hence, they called this kind of synchronization, phase synchronization. Not only laboratory experiments have demonstrated phase synchronization of chaotic oscillators, such as electronic circuits, lasers and electrochemical oscillators, but also natural systems can exhibit phase synchronization. For example, the dynamics of the cardio respiratory system, an extended ecological system, and the electroencephalographic activity of Parkinson patients display synchronization features.

On one hand it is important to investigate the conditions under which coupling of chaotic systems occurs, and on the other hand, to develop tests for the detection of coupling. In this work, it has been concentrated on the second task for the cases of phase synchronization (PS) and generalized synchronization (GS). Several measures have been proposed so far for the detection of PS and GS. However, difficulties arise with the detection of coupling in systems subjected to rather large amounts of noise and/or non-stationarity, which are common when analyzing experimental data. The new measures that will be proposed in the course of this report are rather robust with respect to these effects. They hence allow to be applied to data, which have evaded coupling analysis so far. The proposed tests for synchronization in this work are based on the fundamental property of recurrences using order patterns.

The planned structure of whole project work starts with concept given by Andreas Groth from his paper named as *Visualization of coupling in time series by order recurrence plots* [34]. Previous to this work in the analysis of coupled systems various techniques have been developed to detect cooperative behaviour from observed time series in the following literatures:

Depending on the nature of the systems, there are different requirements to the above methods. While linear methods based on correlations are not sufficient to deal with nonlinear dependencies, most nonlinear methods require sufficiently long stationary time series. For the case that stationarity holds only for short observation time, cross recurrence plots CRPs were introduced in following literatures:

However, the method of CRP is based on taking distances of trajectories, which is conceptually difficult on physically different systems. A general problem in studying multivariate data from natural systems, for instance electroencephalogram EEG data, is that measurement conditions change with time. Among others offset and amplitude range can vary differently within the channels.

To overcome this problem we consider a special symbolic dynamics of the system, where the time series is encoded by order patterns. This yields further symbol sequences, which are invariant with respect to certain distortions in amplitude.

The concept of symbolic dynamics was proposed by Bandt and Pompe [11], they suggested that the symbol sequence should come naturally from the time series, without further model assumptions, and that one should therefore take partitions as given by comparisons of neighbouring values of the series. With this symbolic dynamics Bandt and Pompe suggested a method of complexity measure and successfully applied to epileptic seizure detection in paper given below:

Following the idea of CRPs Andreas Groth introduce a visualization tool based on the recurrence of order patterns.

Thomas Schreiber in his paper, *Measuring Information Transfer* [21], describes a method based on transfer entropy approach using the Markov property. The purpose of this paper is to motivate and derive an alternative information theoretic measure, to be called transfer entropy, which shares some of the desired properties of mutual information but takes the dynamics of information transport into account. With minimal assumptions about the dynamics of the system and the nature of their coupling one will be able to quantify the exchange of information between two systems, separately for both directions, and, if desired, conditional to common input signals. The concept of this is used in our work to generate a modified form of ORP and RP based on Markov property.

3. Methodology:

A major task in bivariate or multivariate data analysis is to compare or to find interrelations in different time series. These data are obtained from natural systems, which show generally non-stationary and complex behaviour providing short data series. Linear approaches of time series analysis are not sufficient to analyze this kind of data. So, a variety of nonlinear techniques has been developed to analyze data of complex systems [7,8]. Most popular are methods to estimate fractal dimensions, Lyapunov exponents [8-11]. However, most of these methods need long data series. To overcome the difficulties with non-stationary and short data series, the method of recurrence plots has been introduced [12-14]. An extension of the method of recurrence plots to cross recurrence plots enables us to observe the time dependent behaviour of two processes which are both recorded in a single time series [15,16]. The basic idea of this non-linear approach is to compare the phase space trajectories of two processes in the same phase space. This section deals with the measures of complexity based on cross recurrence plots.

3.1 Complexity Measures Based On Cross Recurrence Plots

We define some Recurrence Quantification Analysis (RQA) measures for quantifying the similarity between the phase space trajectories. Since we use the occurrence of the more or less discontinuous main diagonal as a measure for similarity, the RQA measures will be determined for each diagonal line parallel to the main diagonal, hence, as functions of the distance from the main diagonal. Therefore, it is possible to assess the similarity in the dynamics depending on a certain delay.

We analyze the distributions of the diagonal line lengths $P_t(l)$ for each diagonal parallel to the main diagonal. The index t $\in[-T, \ldots, T]$ marks the number of the diagonal line, where $t = 0$ marks the main diagonal, $t > 0$ the diagonals above and $t < 0$ the diagonals below the main diagonal, which represent positive and negative time delays, respectively.

The Recurrence Rate (RR) is now defined as:

$$RR(t)=\frac{1}{N-t}\sum_{l=1}^{N-t} lP_t(l) \qquad (1)$$

and reveals the probability of occurrence of similar states in both systems with a given delay t . A high density of recurrence points in a diagonal results in a high value of RR. This is the case for systems whose trajectories often visit the same phase space regions.

The Determinism (DET) is defined as:

$$DET(t)=\frac{\sum_{l=l_{min}}^{N-t} lP_t(l)}{\sum_{l=1}^{N-t} lP_t(l)} \qquad (2)$$

is the proportion of recurrence points forming long diagonal structures of all recurrence points. Stochastic as well as heavily fluctuating data cause none or only short diagonals, whereas deterministic systems cause longer diagonals. If both deterministic systems have the same or similar phase space behaviour, i.e., parts of the phase space trajectories meet the same phase space regions during certain times, the amount of longer diagonals increases and the amount of smaller diagonals decreases.

The average diagonal line length (L) is defined as:

$$L(t) = \frac{\sum_{l=l_{min}}^{N-t} l P_t(l)}{\sum_{l=l_{min}}^{N-t} P_t(l)} \qquad (3)$$

reports the duration of such a similarity in the dynamics. A high coincidence of both systems increases the length of these diagonals.

High values of RR represent high probabilities of the occurrence of the same state in both systems, high values of DET and L represent a long time span of the occurrence of a similar dynamics in both systems. Here DET and L are sensitive to fastly and highly fluctuating data, whereas RR measures the probabilities of the occurrence of the same states inspite of these high fluctuations.

4. Result and Discussion:

A CRP is plotted between a sine wave and a noisy sine wave which is corrupted by a white Gaussian noise. The CRP is plotted with an embedding of m=3, τ=2 and ∈=1.5.

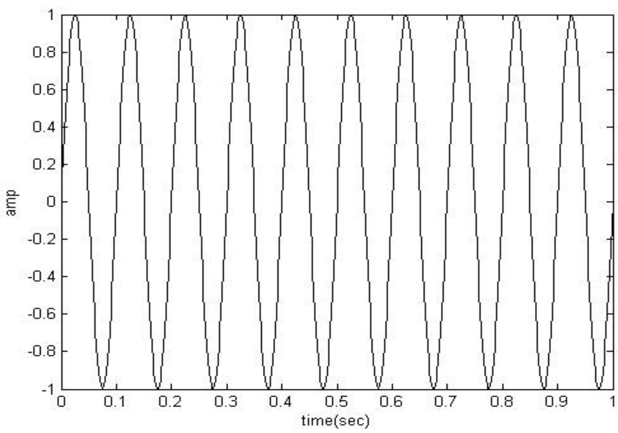

Fig: 1. Sine wave plot

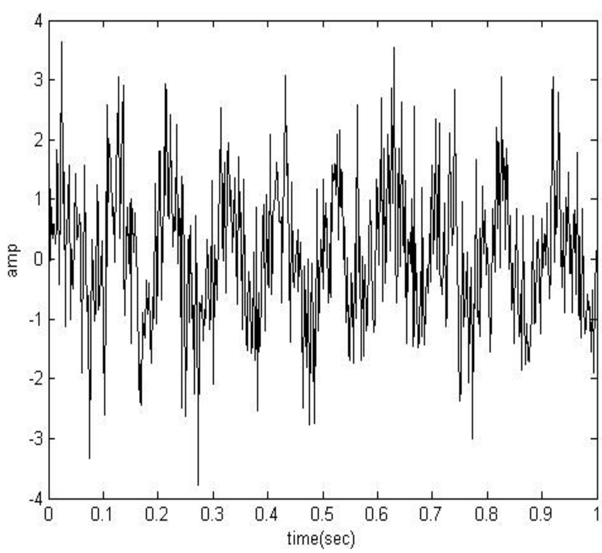

Fig: 2. Noisy sine wave

Fig: 2 shows the plot of noisy sine wave corrupted by the white Gaussian noise.

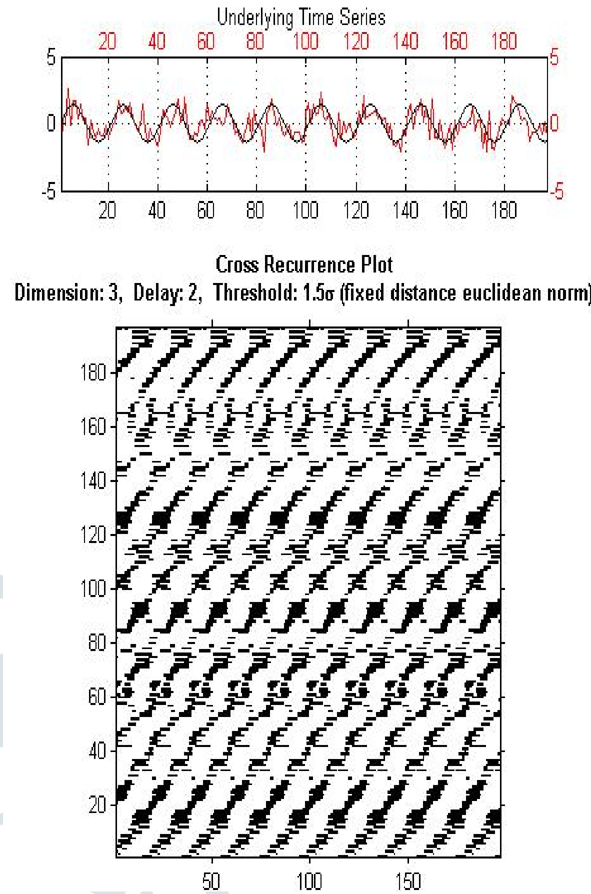

Fig: 3. CRP for sine and noisy sine wave

Fig: 3 shows the CRP between sine wave and noisy sine wave shown in figures 3.1,3.2 by taking the values of embedding parameters dimension=3,delay=2 and threshold=1.5.

The CRP shows diagonal structures separated by gaps. These gaps are the result of the high fluctuation of the noisy sine function. Due to the periodicity of these functions, the diagonals have a constant distance to each other. Due to the noisy data, the trajectories strongly fluctuate in the phase space and thus short diagonal lines in the CRP occur and the diagonal structures are interrupted.

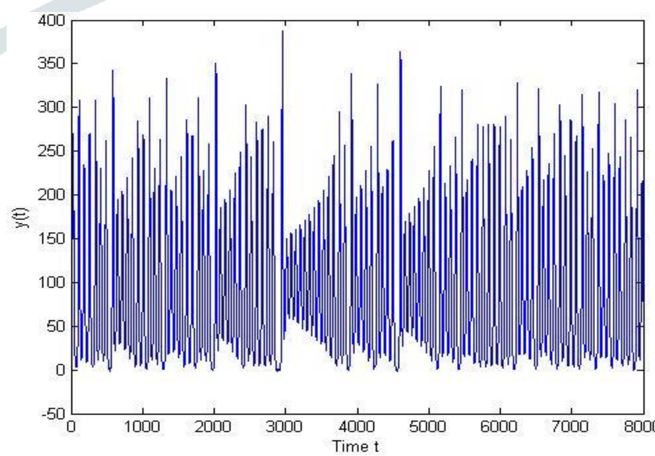

Fig: 4. Forced auto regressive process

Fig: 4 shows the first order auto regressive process driven by a squared x-component of the Lorenz system.

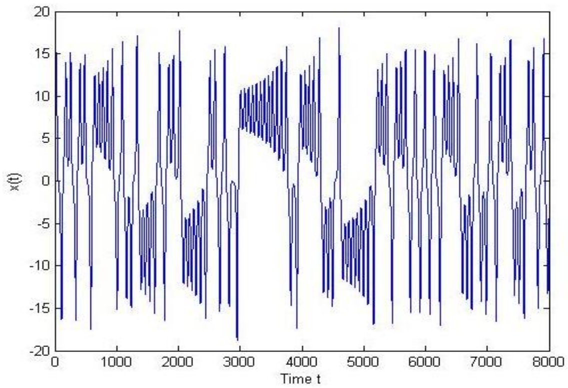

Fig. 5. Lorenz system

Fig: 5 shows the forcing function (x-component of the Lorenz system). And as we know that every dynamical system can be represented by an attractor, which is as follows:

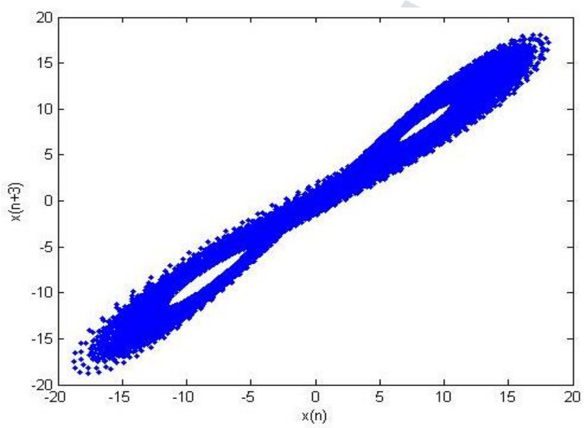

Fig: 6. Attractor plot

Fig: 6 shows the attractor plot for the dynamical system i.e. Lorenz system. Here x and y axis represents the number of samples.

The CRP between y(t) and x(t) is as follows:

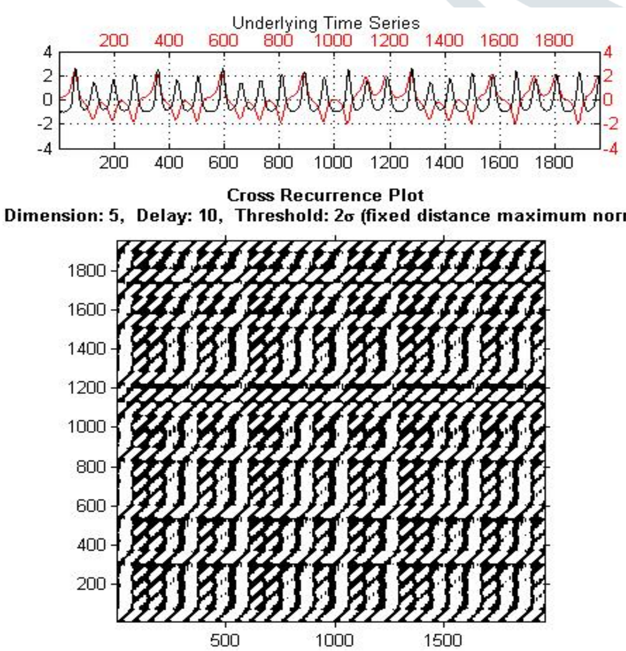

Fig: 7. CRP for y(t) and x(t)

Fig: 7 shows the CRP between the forced auto regressive process and the forcing function (x-component of the Lorenz system) by taking the values of dimension=5, delay=10 and threshold=2. The CRP of the driven AR-process with the x-component of the Lorenz system($m = 5$, $\tau = 10$,$\varepsilon = 2$) contains a lot of longer diagonal lines, which represent time ranges in which both systems have a similar phase space dynamics.

5. Conclusion:

The objective of present work is to study various non linear processing techniques used for detection of index coupling between two interacting systems. In the initial stage properties of phase relations and recurrences are used to find there dependencies on strength of coupling using the phase obtained from analytic signal and from curvature of analytic signal. Then we used order recurrence plot for developing a method of visualizing cooperative behaviour between two coupled dynamical systems. So we can conclude that this method of order patterns based on Markov property can also be used over biomedical signals for finding short time dynamics and they can be more accurate in diagnosis of pathological condition that can be detected from strength of interactions between recorded signals obtained from two structurally different systems like ECG and heart rate variability, breathing patterns and EMG or in between different EEG channels for the patients of Parkinson disease or to analyze sleep disorders by studying EEG during various sleep stages.

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