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Synchronization Index based Epilepsy Diagnosis from EEG Data by Recurrence based Soft Computing Model

Praveen Kumar Singh
Computer Science & Engineering,
A.I.E.T., Lucknow, India
praveenhcst84@gmail.com

Uday Singh
Computer Science & Engineering,
A.I.E.T., Lucknow, India
udayiert@rediffmail.com

***Abstract*--** **A well-known common feature of oscillatory systems and biological oscillators, in particular, is their ability to synchronize. Entrainment of periodic (also noisy) self-sustained oscillators by external periodic force, or mutual synchronization of several such oscillators is well understood and this theoretical knowledge is idly used in experimental studies and in the modeling of interaction between different physiological (subsystems).We investigate synchronization between cardiovascular and respiratory systems in healthy humans under free-running conditions. For this aim we analyze non stationary irregular bivariate data, namely, electrocardiograms and measurements of respiratory flow. We briefly discuss a statistical approach to synchronization in noisy and chaotic systems and illustrate it with numerical examples; effects of phase and frequency locking are considered. Next, we present and discuss methods suitable for the detection of hidden synchronous epochs from such data. The analysis of the experimental records reveals synchronous regimes of different orders and transitions between them; the physiological significance of this finding is discussed.**

Keywords: EEG , Recurrence, Coupling Phenomenon, and Biomedical.

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.

The method of RPs is used to visualise the recurrences of the dynamical systems. Suppose we have a trajectory $\{\vec{x}_i\}_{i=1}^{N}$ of a system in its phase space [1]. The components of these vectors could be position and velocity of a pendulum or quantities such as temperature, air pressure, humidity and many others for the atmosphere. The development of systems is described by a series of these vectors, representing a trajectory in an abstract mathematical space. Then the corresponding recurrence plot is based on the following recurrence matrix:

$$R_{i,j} = \begin{cases} 1 : & \vec{x}_i \approx \vec{x}_j \\ 0 : & \vec{x}_i \not\approx \vec{x}_j \end{cases}, \quad i , j = 1,2,3.......N \qquad (1)$$

where N is the number of considered states and $\vec{x}_i \approx \vec{x}_j$ means equality upto an error ε**.** This ε is essential as systems often do not recur exactly to a formerly visited state but just approximately. The matrix compares the states of a system at times i and j. If the states are similar, this is indicated by a one in the matrix, i.e. $R_{i,j}$=1. If on the other hand the states are different, the corresponding entry in the matrix is $R_{i,j}$=0. So the matrix tells us when similar states of the considered system occur. Thus representation of the recurrence matrix, gives the patterns of recurrences and allows us in studying dynamical systems and their trajectories. The "points" of the phase space represent possible states of the system. Let us say that the state of such a system at a fixed time t can be specified by d components.

These parameters can be considered to form a vector

$$\vec{x}(t) = (x_1(t), x_2(t), \ldots\ldots, x_d(t))^T \qquad (2)$$

in the d-dimensional phase space of the system.

2 Recurrence Plot

As our focus is on recurrences of states of a dynamical system, we define now the tool which measures recurrences of a trajectory $\vec{x}_i \in R^d$ in phase space: the recurrence plot,

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Eq.(3.1) [1]. The recurrence plot efficiently visualises recurrences of the states of the dynamical system and can be expressed by the matrix,

$$R_{i,j}(\epsilon) = \Theta(\epsilon - \|\vec{x}_i - \vec{x}_j\|) \quad , \quad i, j = 1,2,3,\ldots\ldots\ldots,N. \qquad (3)$$

where N is the number of measured points $\vec{x}_i$, ϵ is the threshold distance, $\Theta(.)$ the Heaviside function (i.e. $\Theta(x) = 0$ if $x<0$ and $\Theta(x) = 1$ otherwise), and $\|.\|$ is a norm. For ϵ - recurrent states i.e. for states which are in ϵ neighbourhood we introduce the following notation:

$$\vec{x}_i \approx \vec{x}_j \quad \Longleftrightarrow \quad R_{i,j} \equiv 1 \qquad (4)$$

The RP is obtained by plotting the recurrence matrix, and using different colours for its binary entries, e.g., plotting a black dot at the coordinates (i,j), if $R_{i,j} \equiv 1$ and a white dot, if $R_{i,j} \equiv 0$. Both axes of the RP are time axes. Since $R_{i,j} \equiv 1 |_{i=1}^{N}$ by definition, the RP has always a black main diagonal line which is called the Line of Identity (LOI). In order to compute an RP, an appropriate norm has to be chosen. The most frequently used norms are the L_1-norm, the L_2-norm (Euclidean norm) and the L_∞-norm (Maximum or Supremum norm). To compute RPs, the L_∞-norm is often applied, because it is computationally faster and allows us to study some features in RPs analytically.

3 Cross Recurrence Plot

The CRP is a bivariate extension of the RP and was used to analyse the dependencies between two different systems by comparing their states [2,3]. It can be considered as a generalisation of the linear cross-correlation function. Suppose we have two dynamical systems, each one represented by the trajectories $\vec{x}_i$ and $\vec{y}_j$ in a d-dimensional phase space. The corresponding cross recurrence matrix is defined by,

$$CR_{i,j}^{\vec{x},\vec{y}}(\epsilon) = \Theta(\epsilon - \|\vec{x}_i - \vec{y}_j\|) \quad , \quad i = 1,2,\ldots.,N \quad ; \quad j=1,2,\ldots.,M \qquad (5)$$

where the length of the trajectories of $\vec{x}$ and $\vec{y}$ is not required to be identical, and hence the matrix CR is not necessarily square. Both systems are represented in the same phase space, because a CRP searches for those times when a state of the first system recurs to one of the other system. This bivariate extension of the RP was introduced for the Cross Recurrence Quantification [2]. The concept of CRPs is also used to study interrelations between time series [4]. The lines which are diagonally oriented are of major interest. They represent segments on both trajectories, which run parallel for some time. A measure based on the lengths of such lines can be used to find nonlinear interrelations between two systems which cannot be detected by the common cross-correlation function [3]. Assuming two identical trajectories, the CRP coincides with the RP of one trajectory and contains the main black diagonal or LOI. If the values of the second trajectory are slightly modified, the LOI will become somewhat disrupted and is called LOS. However, if we do not modify the values but stretch or compress the second trajectory slightly, the LOS will still be continuous but not a straight line. This line can become bowed.

4 Synchronization Analysis Using Recurrences

Any two systems are said to be phase synchronized when their respective frequencies and phases are locked. Studies have been made about the chaotic phase synchronization (CPS) which has been mainly observed for coherent oscillators. But when dealing with non-coherent oscillators, it is unclear whether some phase synchronized state can be achieved. To treat this problem, we propose a method based on recurrences in phase space that allows us to quantify indirectly CPS, which even works in the case of noisy non-coherent oscillators.

Next we study about Generalized Synchronization (GS) and recurrences. Two systems x(t) and y(t) are said to be in GS when two close states in the phase space of x correspond to two close states in the phase space of y. Hence the neighbourhood identity in phase space is preserved. Since the recurrence matrix $R_{i,j}^{(\varepsilon)}$ is nothing else as a record of the neighbourhood of each point of the trajectory, we can conclude that two systems are in GS if their RPs are almost identical. Thus the GS between considered oscillators is estimated using the generalized synchronization and recurrences. In order to detect GS the indices JPR and SPR have been introduced.

5. The Line of Synchronization in the CRP

From the conventional Recurrence Plot, one always finds a main diagonal in the plot, because of the identity of the (i,i)-states. The RP can be considered as a special case of the CRP, which usually does not have a main diagonal as the (i,i)-states are not identical. A CRP of the two corresponding time series will not contain a main diagonal. But if the sets of data are similar, a more or less continuous line in the CRP that is like a distorted main diagonal can occur. A CRP of a sine function with itself (i.e. this is the RP) contains a main diagonal.

Now, we rescale the time axis of the second sine function in the following way:

$$\sin(\varphi t) \rightarrow \sin(\varphi t + a \sin(\psi t)) \qquad (6)$$

we will use the notion rescaling only in the mention of the rescaling of the time scale. The rescaling of the second sine function with different parameters φ results in a deformation of the main diagonal. The distorted line contains the information on the rescaling, which we will need in order to re-synchronize the two time series. Therefore, we call this distorted diagonal, LOS.

The plot of a sine function and its corresponding CRP is as follows:

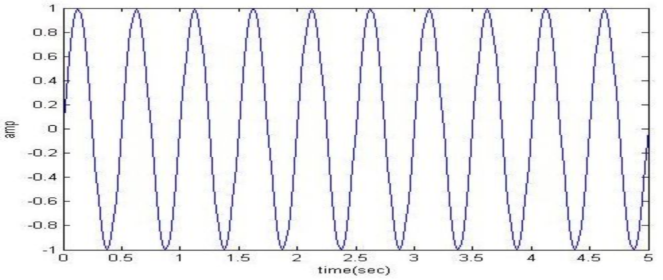


Fig. 1. Plot of a sine function sin(φt)

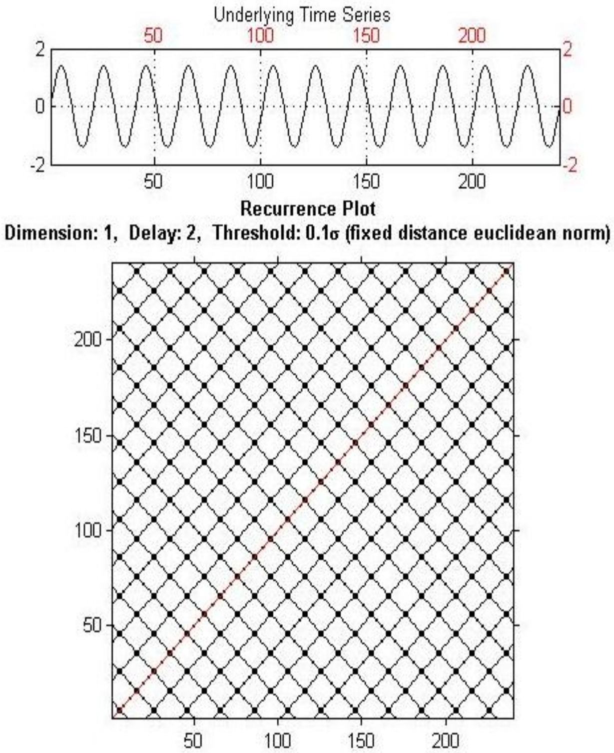


Fig. 2. CRP between the two sine functions shown in fig. 1.

6. Result and Discussion:

6.1 Phase Synchronization by Means of Recurrences

Here we consider a different approach based on recurrences in phase space to detect and quantify CPS. The concept of recurrence in dynamical systems goes back to Poincare [5], when he proved that after a sufficiently long time interval, the trajectory of an isolated mechanical system will return arbitrarily close to each former point of its route.

We define the recurrence of the trajectory of the dynamical system $\{\vec{x}_i\}_{i=1}^{N}$ in the following way: we say that trajectory has returned at time t=j to the former state at t=i if

$$R_{i,j}^{(\varepsilon)}=\Theta(\varepsilon-\| \vec{x}_i - \vec{x}_j \|) = 1, \qquad (7)$$

where ε is a pre-defined threshold and Θ is a Heaviside function. Based on this definition it is straightforward to estimate the probability $P^{(\varepsilon)}(\tau)$ that the system returns to a neighbourhood of a former point $\vec{x}_i$ of the trajectory (the neighbourhood is defined as a box of size ε centered at $\vec{x}_i$, as we use the maximum norm) after τ time steps.

$$\hat{P}^{(\varepsilon)}(\tau)=\frac{1}{N-\tau}\sum_{i=1}^{N-\tau}\Theta(\varepsilon-\| \vec{x}_i-\vec{x}_{i+\tau} \|)=\frac{1}{N-\tau}\sum_{i=1}^{N-\tau}R_{i,i+\tau}^{(\varepsilon)} \qquad (8)$$

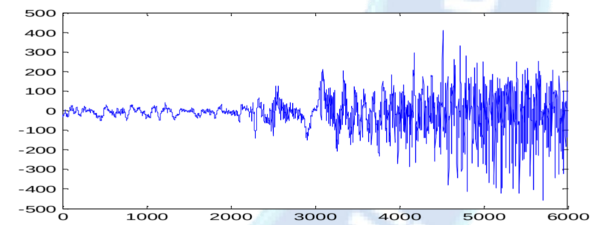
This function can be considered as a generalized autocorrelation function, as it also describes higher order correlations between the points of the trajectory in dependence on time delay τ. $\hat{P}^{(\varepsilon)}(\tau)$ is determined for a trajectory in phase space. Further it is possible to reconstruct the attractor by only considering the recurrences of single components of the system [6]. Because of this it is possible to estimate dynamical invariants of the system (e.g., entropies and dimensions) by means of recurrences in phase space, i.e. the recurrences of the system in phase space contain information about higher order dependencies within the components of the system. This method has been successfully applied to geophysical data [7]. For a periodic system in phase space, the probability of recurrence P(τ) is equal to 1 if τ is equal to a multiple of the time period T of the system, and 0 otherwise.

6.2 Application of RP to EEG signals recorded during epileptic seizure:

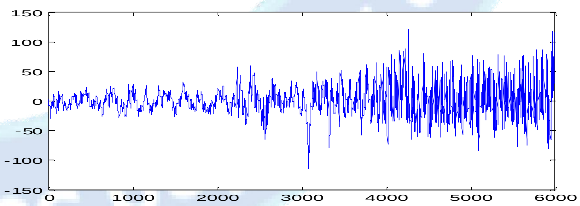
Since this new RP is sensitive towards variation in coupling so we can apply it on passive experiments, where we do not have direct control over coupling strength e.g. on EEG under epileptic seizure.

Two EEG signals are taken from different channels and a sliding window is applied as showing in Fig. 3 (c, d, e, f, g) t here are RP of EEG at different moments. It is found that density of black dots is diminishing as we move towards seizure moments and eventually RP has very rare white black dots at the seizure activity in Fig. 3 (f, g).

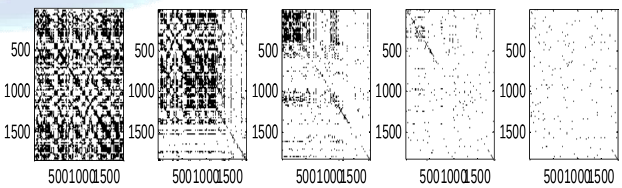
This is also shown through recurrence rate rr (t) and coupling index ρ_π in next figures.



3a



3b



3c 3d

3e 3f 3g

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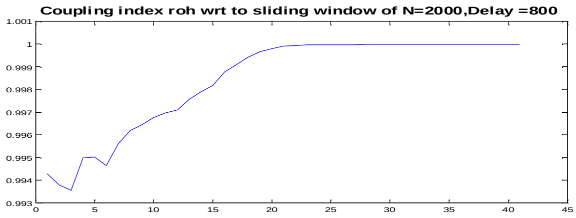


3h

Fig. 3. (a, b) EEG signals, (c, d, e, f, g) corresponding RP_{Markov}'s with sliding window N=2000, delay=800, m=3, τ=4, and 3 (h) is plot for ρ_π (t).

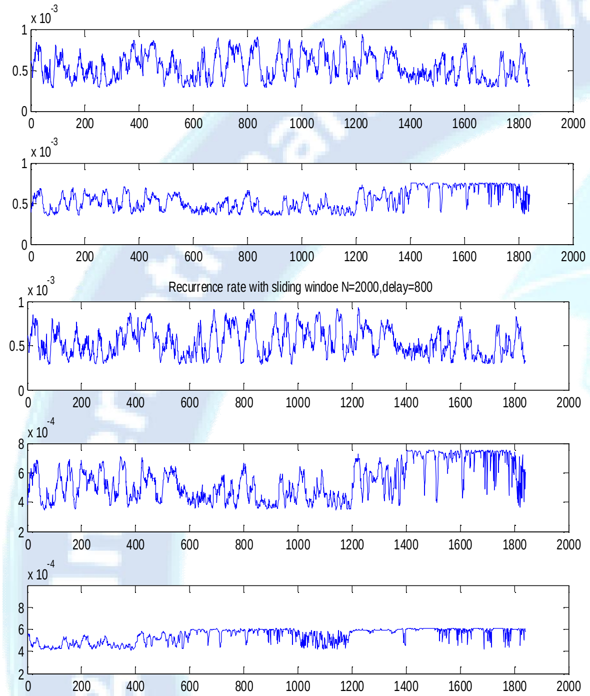
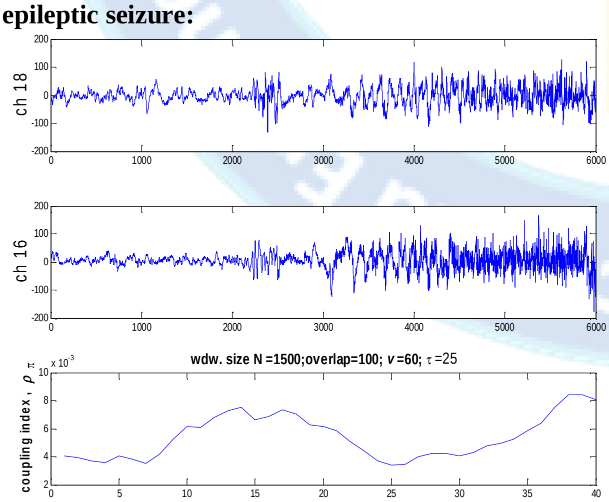


Fig. 4. Recurrence Rate rr(t) for RP_{Markov}

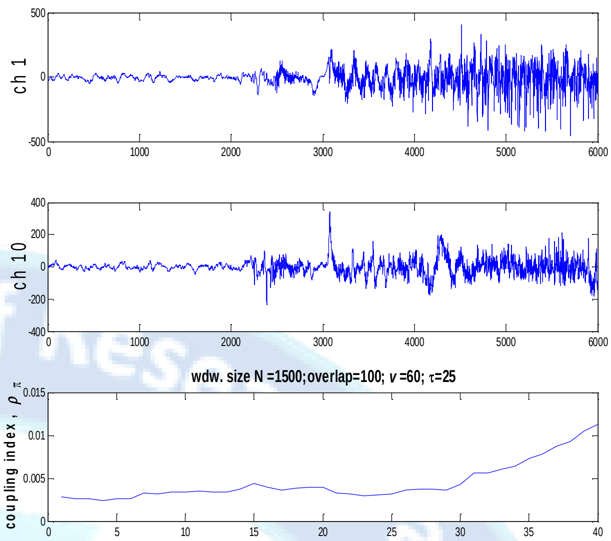
6.3 Order Recurrence plot of order patterns

$$ORP_M(i, j) = 1; \quad \text{if } \pi_x(i) = \pi_y(j) \quad \text{else } 0; \quad i, j = 1 \ldots N \qquad (9)$$

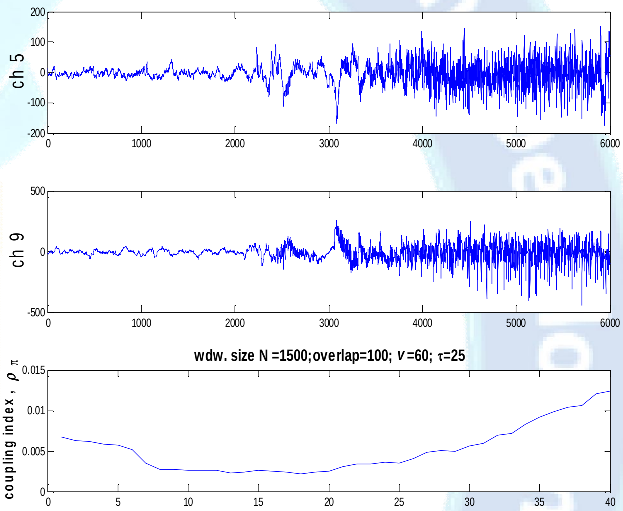
6.7 Application of ORP_M to EEG signals recorded during epileptic seizure:



(a)



(b)



(c)

Fig. 5. Application of ORP_{Markov} on different combination of EEG signals for detecting coupling.

After checking the performance of ORP_M over Rossler system with variation in coupling index. It is obvious that ORP_M is able to detect the coupling strength we applied it on the EEG signal recorded under epileptic seizure as shown in Fig. 4.19 with different combination three different combinations of channels (a) channel 15 and 18, (b) channel 1 and 10 and (c) channel 5 and 9 along with coupling index ρ_π initially in normal condition ρ_π is small and as the sliding window moves under the duration of epileptic seizure ρ_π gradually increases in 5 a, b and c. Same analysis is done with other different combination and all are showing the same behaviour of ρ_π for all combinations. It proves that inclusion of Markov property in defining order pattern according to Equation 5 is capable of detecting coupling in EEG signal and it demonstrate clear differences in uncoupled, weakly coupled and strongly coupled conditions.

7. Conclusion:

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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