JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

AutomatedDetection of Epilepsy by Improved Recurrence Parameter

Divya Pandey
Communication Engineering,
KNIT, Sultanpur, India
erdivya917@gmail.com

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 using artificial neural network (ANN) is performed with other techniques in detection of the coupling direction in lightly and strongly coupled systems.

Keywords: CRP, EEG, Recurrence Rate, RQA,ANN

1. Introduction:

Many dynamical systems have recurrence as a fundamental property. The system's behaviour in phase space is characterised using this recurrence feature. Recurrence is a notion used in data processing and the research of dynamical systems. It is a useful tool for visualising and analysing dynamical systems that was developed by Poincare [1]. As a result, recurrences include all necessary data regarding the functionality of the device. The Recurrence Plots (RPs) approach is expanded to CRPs. The CRP approach allows us to investigate synchronisation or temporal disparities between two distinct time series, as evidenced by the LOS, a distorted principal diagonal in the CRP. 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 article and their applications to biomedical signals using the ANN are 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 oscillatorsand 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 using ANN as classifier 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 analysis of synchronisation or timing discrepancies across two time series is possible with Cross Recurrence plots. In the cross recurrence plot known as the LOS, this is highlighted by a distorted primary diagonal. We discovered an interesting property of CRPs by their method. Besides from the possibilities of using recurrence quantification analysis [2], there is a closer relationship between CRP structures as well as the systems under consideration. Finally, this function can be used to perform data set synchronisation. The data series must be synced to the similar time scale prior any time series analysis can be performed. This is often accomplished by comparing and correlating two sets of data. There have been some suggestions for this type of correlation as well as modification [5].

The symbol-based recurrence graphic shows patterns that are typical of dynamical behaviour [1,6]. A stochastic process is revealed by a group of single recurrence points dispersed uniformly as well as unevenly through the entire design. Periodic processes produce larger, parallel diagonals generated by recurrence points by means of the similar space among them. The shift in the amplitude of the system can be seen by paling the RP aside as of the larger diagonal and toward corners. The RP's vertical and horizontal white bands are caused by states that occur seldom or reflect extreme levels. If a condition doesn't really change for a long time, such as laminar states, extended horizontal as well as vertical black lines or regions appear. The property of recurrence of states was used to create all of these entities. The states are stated to be just "the same," and recurrence is determined by distance ε.

2. Related Work:

The study of linked system began in the 17th century with a consideration of synchronisation of nonlinear periodic systems. The synchronisation of separate pendulum clocks strung along the same beams (Huygens found synchronisation using this configuration), Nymphs blinking in time, or the idiosyncrasies of adjacent organ pipes that can effectively annihilation or communicate in synchronization, are all well-known examples. Researchers did not find until the 1980s shows 2 different chaotic networks could remain fully linked, meaning their time progression is identical. The construction of encrypted communication gadgets has been altered as a result of this revelation. Messages can be masked and overheard using synchronised chaotic trajectories. This study extends the concept of perfect synchronisation of chaotic systems by allowing non-identity between linked systems. A few years later, Rosenblum et al. [1] looked at a relatively minor degree of synchronisation among chaotic oscillations, during which their linked phases synchronise although overall amplitudes remain largely uncorrelated. As a result, the term "phase synchronisation" was coined to describe this kind of synchronisation. Chaotic oscillators, like electronic circuits, lasers, and electrochemical oscillations, have been shown to phase synchronise not only in laboratory research but also in natural systems. The cardiopulmonary and respiratory systems are as well as the prolonged environmental system as well as electroencephalographic action of Parkinson's patients, all exhibit synchronisation qualities.

On the one hand, it is crucial to examine the situations within which chaotic systems couple, and then on the other, to design methods for coupling identification. For the situations of phase synchronisation (PS) and generalised synchronisation (GS), the focus of this study has been on the second job (GS). Several methods for detecting PS and GS have been developed thus far. However, detecting coupling in structures a matter of substantial quantity of noise and/or non-stationary, which is typical as soon as reviewing experimental information, can be difficult. In terms of these impacts, The additional measurements which would be recommended as part of such research are fairly reliable. As a result, they can be applied to data that have hitherto eluded coupling investigation. The synchronisation tests provided in this paper are predicated on a basic characteristic of recurrences employing order pattern.

Andreas Groth's idea of Visualization of couplings in time series using order recurrence plots [34] is the foundation for the entire project's defined framework. Various strategies for detecting cooperative behaviour from observational time series have been established prior to this study in the study of coupled systems in the following literatures.

The above methods have varied requirements based on the nature of the systems. While correlation-based linear methods are insufficient for dealing most nonlinear approaches necessitate large stationary time series for dealing on nonlinear relationships.. Cross recurrence plots (CRPs) were presented in the second literatures for the case where stationary only holds for a brief observation time:

The CRP technique, on the other hand, is reliant on calculating trajectories' distances, which is theoretically challenging on physically dissimilar systems. The fact that measurements conditions change over time is a common challenge when evaluating multivariate informationoriginating in natural processes, such as electroencephalogram EEG records. Within in the channels, offset as well as amplitude range, for example, can differ.

To overcome this problem, we examine a particular symbolic dynamics of the systems in which the time series is represented by order patterns. This produces additional symbolism sequences that are unaffected by amplitude distortions.

Bandt and Pompe [11] presented the notion of representational dynamics, arguing that symbol order should emerge spontaneously without taking into account the time series the need for additional model requirements, and that divisions should be determined by comparing adjacent series values. Bandt and Pompe proposed a method of complexity measurement based on this symbolic dynamics, which they effectively implemented to epileptic seizure detection in the study below:

Andreas Groth introduces visualisation device predicated on the recurrence of instructionarrangements, based on the idea of CRPs.

In his paper Measuring Information Transfer [21], Thomas Schreiber pronounces a strategy depending on transfer entropy and Markov property. The aim of the research is to inspire as well as develop transfer entropy, a new data theoretic measurement that combines most of its beneficial properties underlying mutual information while also accounting for the dynamics of information transmission. With only a few assumptions about the system's dynamics and the nature of their coupling, The transfer of message across two devices can be quantified in both directions, even conditionally on shared incoming signal if necessary. In our study, we employ this approach to produce aimproved variant of ORP as well as RP depending on the Markov property.

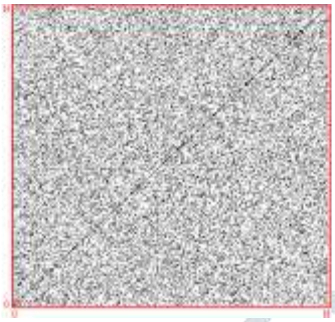
3. Methodology:

The idea of recurrence times return to Poincare[24], which established that the trajectory of a chaotic structure in phase space After a sufficiently prolonged period, it will repeat arbitrarily near to any prior place on its path having probability one. The idea of recurrence in the context of chaotic systems was not studied again until the 1960s, when Lorenz discovered three ordinary differential equations that display chaotic behaviour [25]. Lorenz discussed "natural occurring analogues" in [26], which are dynamical states that are substantially similar to situations that have occurred in the past. He presented various algorithms to forecast the future evolution of dynamical systems based on this approach.

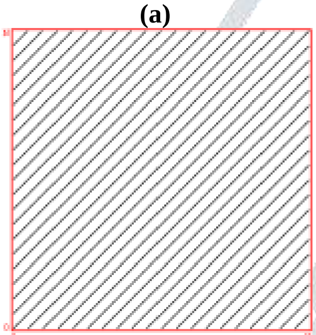
Later, Eckmann et al. invented the recurrence plots (RPs) method, which visualises a dynamical system's recurrences and provides details on the trajectory's behaviour in phase space. As a result of adaptability to short as well as non-stationary time series, this approach has gained popularity in recent years. Furthermore, [27, 28, 29, 30, 31, 32, and 33] have addressed a more fundamental analysis of the connection among RPs as well as the attributes of dynamical systems.

However, there are still unsolved issues, such as the application of the concept of recurrence to the study of the link among interacting systems, which has not been well examined from a theoretical standpoint. The coupling properties of chaotic systems are connected to the recurrences of two interacting systems in this report. The synchronisation index is calculated using ANN utilising these features. Following an introduction to the RPs approach, "order recurrence plots" is offered as a modified method for calculating recurrence plots of multivariate time series. This technique differs significantly from the previous method proposed for bivariate time series analysis in that it allows for the estimate of dynamical invariants of interacting subsystems. Although this method can be used to investigate any coupled system, it has been focused on the research of chaotic system synchronisation using order recurrences and the inclusion of the Markov property. However, this study is only useful when the parameters of the system under discussion can be altered in a systematic manner, and it takes a long time. They are ideal as test statistics for the conduct of a hypothesis test because they accurately show the commencement of PS and, accordingly, GS. They have the benefit that they may be used for systems with a lot of phase dispersion, as the classic Rossler system in the funnel regime. Furthermore, the suggested indices are practical in that they enable for the detection of synchronisation in time series that have been heavily contaminated by noise and non-stationary. The ANN is then used to perform an assessment based on these measurements using experimental data from EEG signals.

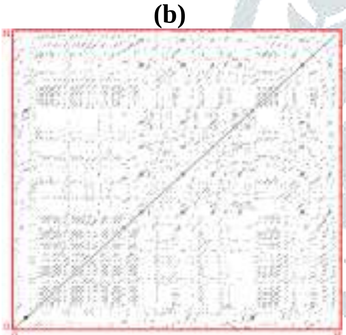
3.1. Recurrence Plots



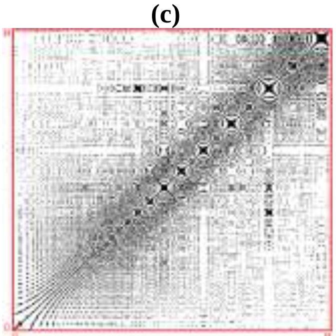
(a)



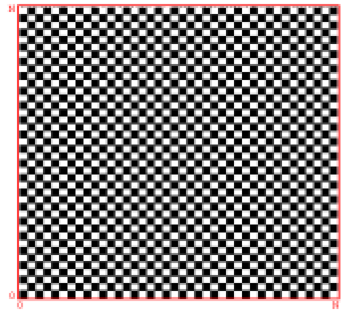
(b)



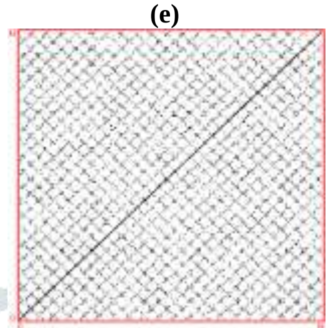
(c)



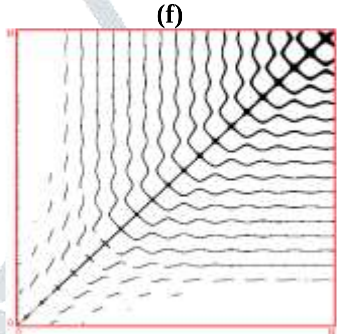
(d)



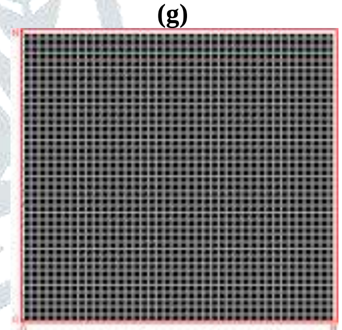
(e)



(f)



(g)



(h)

Fig. 1.(a) Random Series (White Noise), (b) Periodic Sinusoid, (c) Chaotic Series, $X = 4 * X_{n-1} (1 - X_n)$, (d) Linearly Swept Chirp, (e) Delta Function Train, (f) Sinusoid + noise, (g) Square Wave, (h) Decaying Sinusoid

Table 1: Recurrence Plot and there extensions.

Recurrence Matrix	Cross Recurrence Matrix	Joint Recurrence Matrix	Order Recurrence Matrix
$R_{ij} = \Theta(\varepsilon - \parallel x_i - x_j \parallel)$	$CR_{ij} = \Theta(\varepsilon - \parallel x_i - y_j \parallel)$	$JR_{ij}^{xy} = R_{ij}^{x} * R_{ij}^{y}$	ORP(t, τ)=1, $\pi_x(t) = \pi_y(t+\tau)$ 0, otherwise * $\pi_x(t)=1$, if $x(t) > x(t+\tau)$

			τ=delay

We used a simplified version of as shown here for short time constraints:

$$ORP(t,\tau) = \begin{Bmatrix} 1 \text{if} \pi_x(t) = \pi_y(t+\tau) \\ 0 \text{otherwise} \end{Bmatrix} 3.2$$

This confines the scope of the research to a region along the major diagonal. The diagonal lines in Fig.2 are converted to horizontal lines, making it easier to investigate a larger time span.

3.2RecurrenceRate:
UsingtheR(t,τ)wehaveusedtherecurrencequantificationanalysis (RQA)[35,36].
Inanalysisoftimeseriesrecurrencequantificationanalysishasbenefitsthat It is lesser sensitive to the size of the data set as well as does not require steady data, making it appropriate for studying physiological systems with state changes as well as transients..

VariousmeasureswhicharedrawninRQAaregivenbelowwiththeirbriefapplication:

- PercentRecurrence(PR)=rationofno.ofrecurrencepointstototalpoints(i.e.recurrence points occupying a certain % of the plot).
- PercentDeterminism(PD)=the number of recurrence points that form a diagonal line that is higher than a threshold divided by the total number of recurrence points.
- Entropyofrecurrence=Shannonentropyofdiagonalsegmentlength variation
  $=-\sum(p_i.\log p_i)$.
  Here$p_i$istheprobabilityofdiagonallengthlargerthanthreshold level

ImportantfeatureswhichcanbeextractedfromtimeseriesusingRQAare:

- ER:Distributionofrecurrencepointsformingdiagonalline,It's a degree of how complicated the interference dynamics are, forRPitindicatescomplexityofRP.
- IncreaseinsynchronizationbetweensignalsmarkedasincreaseinPR,PD&ER.
- The ratio variables tend to grow throughout physiological transitions as well as tend to settle down whenever a novel quasi-steady-state is attained.
- If the Max Line value is 0, it identifies the existence of probable singularity due to non-deterministic dynamics.

PD&ERarebetterthanPRduetolowersensitivitytonoise (sincerandomnoiseconverselyincreasetheisolatedrecurrencept,coupledsignalsx(i)andy(i)like.).InRPhigherandclearervisibilityofdiagonalindicateshighersynchronization.RQAincludestimedata.It's good at recognising transients and time-varying processes fast.RQAcandetect“unstablesub-harmonicphaselocking”whilepowerspectralanalysiscan otdoso.HenceRPcanbeusedforquantifyingtransientinterferenceinphysiologicalrhythms.(*sub-harmonicindicatespushing term frequency to be almost double that of self-oscillations.*In a recurrence plot, Ratio as well as Trend addressed non-stationary properties).

We start with the fundamental measureas well as plot the number of dots in the ORP as a function of time t. The recurrence rate of order patterns (RR) is what we identify it by analogy, and rr (τ) is the normalised recurrence rate. It is a statistical amount of how identical two dynamical structuresare.

$$RR(\tau) = \sum_t R(t,\tau) \ (1)$$

$$rr(\tau) = RR(\tau) \Big/ \sum_\tau RR(\tau) \ (2)$$

3.3MeasurementofPhaseCoupling:

3.3.1CouplingIndexρ_π(t):
Normalizedrecurrenceraterr(τ)isusedtomeasurethecouplingindexρ_π(t)byusingaslidingwindow.

$$\rho_\pi = 1 - \frac{-\sum_{\tau=\tau_{min}}^{\tau_{max}} rr(\tau)\ln rr(\tau)}{\ln(\tau_{max}-\tau_{min})} (3)$$

τ_{max}=25andτ_{min}=-25forEEGsignals.
➔Thisprovides$0\le\rho_\pi\le1$,wherever:
ρ_π=0matchestonocoupling.
➔It's also been discovered that the coupling index is unaffected by time delays.

3.3.2CouplingIndexρ_H(t):
The distribution of instantaneous phase differences is used to define a coupling index.
$\Delta\Phi_H(t)=[\Phi^1_H(t)-\Phi^2_H(t)]\text{mod}2\pi$

The Shannon entropy S_H can be used to analyse it.
$\rho_H=1-S_H/S_{max}$
where$S_H$istheentropyofthedistributionof$\Delta\Phi_H(t)$.
S_{max}=lnmthemaximumentropyofmbins.
$z(t)=x(t)+i.\tilde{x}(t)=A(t).e^{i\Phi_H(t)}$,$\tilde{x}(t)$istheHilberttransformofx(t)andz(t)is an analytic signal that can be used to determine the phase of signals.

Though, utilising H(t) to interpret a phase is only valid for narrowband transmissions. As a result, the EEG signals are filtered using a band-pass filter. When applied to filtered signals in a movable window of length L=1200, the result is H (t). Signals are band pass filtered (Butterworth Filter, 8-13 Hz for EEG signals) to obtain a qualitatively similar shape to that of (t), i.e. the time of capture is not trustworthy in the case of H without filtering (t).

3.3.3CouplingIndexρ_c(t):
An arbitrary curve's curvature with Ø(t)=arctan x(t)/y(t) was presented as an alternate technique for non-phase-coherent oscillators. However, this method is limited to systems in which we can obtain at least two components. The curvature of an analytic signal was used to add a phase in this way:
$\text{Ø}(t)=\arctan h\{\dot{x}\}/\dot{x}$**;** h{}➔Hilbert transform (4)

wherever a single component is all that is required The coupling strength is determined in the same way as H from phase differences $\Delta\text{Ø}_c(t)=[\text{Ø}^x_c(t)-\text{Ø}^y_c(t)]\text{mod } 2\pi$ Using Shannon entropy $\rho_c = 1- S_c/S_{max}$, **(5)**
through Sc entropy of distribution of $\Delta\text{Ø}_c(t)$.
For direction patterns CMI is:

$$I_{X,Y}^\pi = I(\pi_X(t) ; \Delta_\tau \pi_Y \mid \pi_Y(t)) \text{ and } I_{Y,X}^\pi = I(\pi_Y(t) ; \Delta_\tau \pi_X \mid \pi_X(t)) \quad (6)$$

4. Result and Discussion:

4.1Order pattern Equation:$\pi_x$and π_y are order patterns then the ORP (t, τ) i.e. order recurrence plot for small time dependencies over τ will be. ORP (t, τ) is evaluated from ORP equation given in Table 1.

$ORP\ (t,\tau) = 1, \text{if } \pi_x\ (t) = \pi_y(t+\tau), \text{otherwise } 0$;

$* \pi_x\ (t) = 1, \text{if } x(t) > x(t+\upsilon)$, otherwise 0

;

$ORP(t, \tau) = 1, \text{ if } \pi(t) = \pi(t+\tau)$

0, otherwise

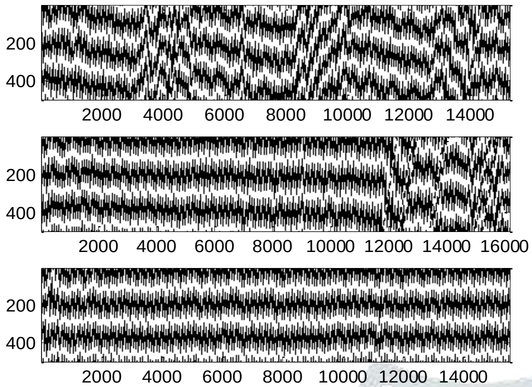


Fig. 2: ORP (t, τ) based on Equation at different strength k=0, 0.027 and 0.037.

Recurrence Rate: $RR(t)=\sum ORP(t,\tau)$

and NormalizedRecurrence Rate, $rr(t)=RR(t)/ \sum RR(t)$

Coupling Index: $\rho_\pi = 1 - \frac{-\sum_{\tau_{min}}^{\tau_{max}} rr(\tau)*\ln(rr(\tau))}{\ln(\tau_{max}-\tau_{min})}$;

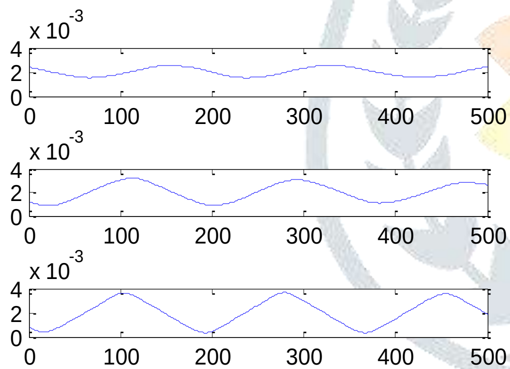


Fig. 3:rr (t) from Equation for ORP at coupling strength k=0, 0.027 and 0.037.

4.2 Application of RPto 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 data from distinct channels are obtained and a sliding window is performed, as shown in Fig. 4, which shows the RP of EEG at various moments. As we go closer to seizure moments, density of black dots decreases and RP ultimately has only a few white black dots at the seizure activity figure 4. The recurrence rate rr (t) as well as coupling index in the subsequent figures likewise demonstrate this.

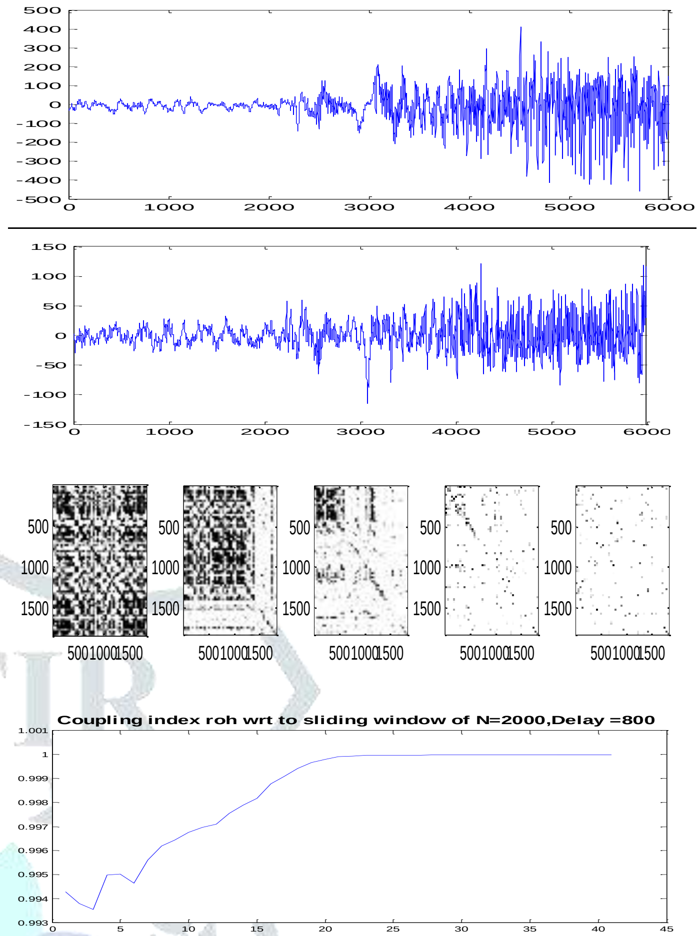


Fig. 4: EEG signals, corresponding RP$_{Markov}$'s with sliding window N=2000, delay=800, m=3, τ=4, and plot for ρ_π (t).

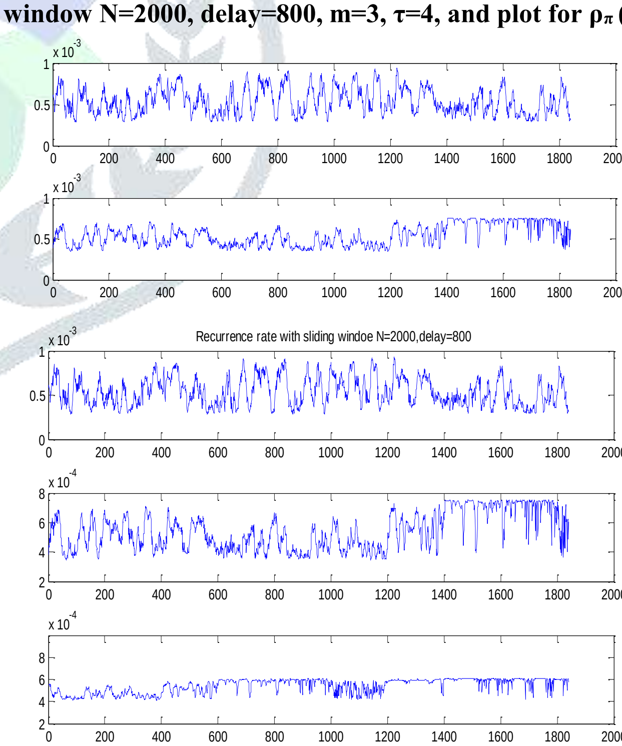
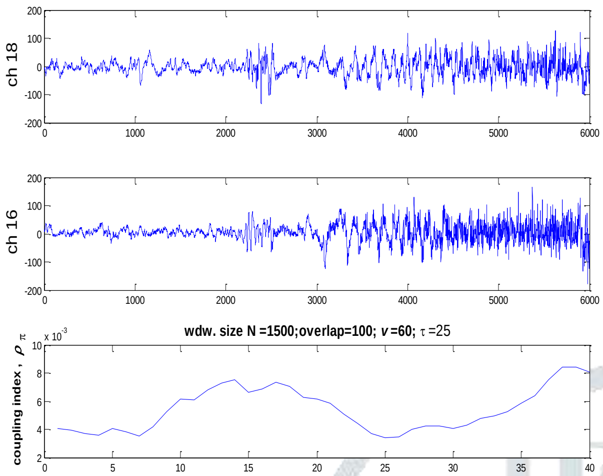


Fig. 5: Recurrence Rate rr(t) for RP$_{Markov}$ for EEG in normal conditions while during transition towards seizure here rr(t) under seizure is higher than rr(t) of normal EEG

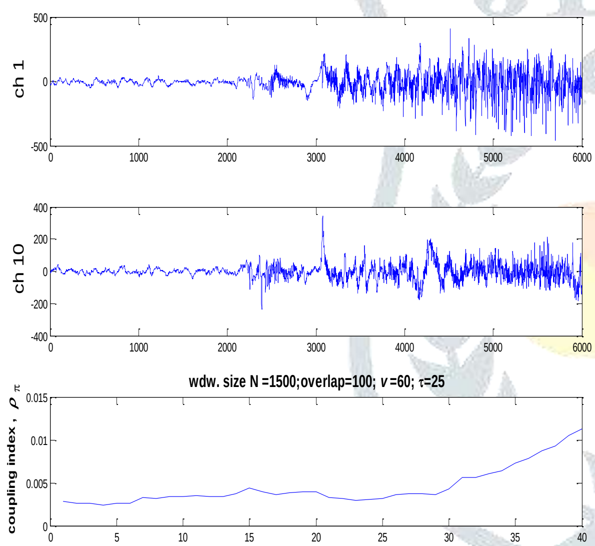
4.3.Order Recurrence plot of order patterns using ANN

ANNORPM (i , j)= 1; if π_x (i) = π_y(j) else 0; i , j=1….N (4.18)

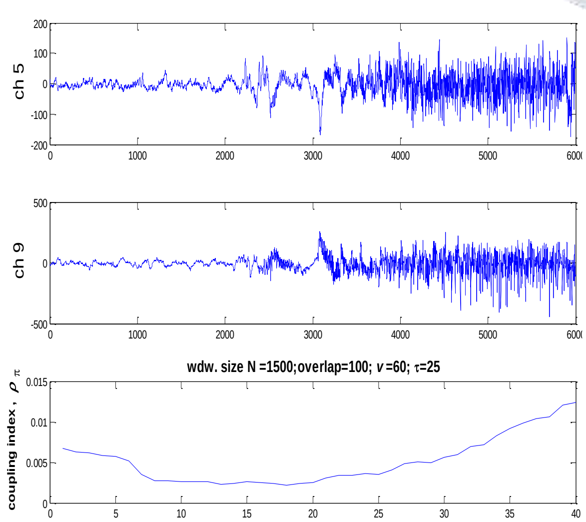
4.4 Application of ANNORPM to EEG signals recorded during epileptic seizure:



(a)



(b)



(c)

Fig. 6: Application of ANNORPM$_{arkov}$ on different combination of EEG signals for detecting coupling.

After checking the performance of ANNORPM over Rossler system with variation in coupling index it is noticeable that ANNORP$_M$ is able to detect the coupling strength we applied it on the EEG signal recorded under epileptic seizure as shown in Fig. 6 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. 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 is capable of detecting coupling in EEG signal and it demonstrate clear differences in uncoupled, weakly coupled and strongly coupled conditions using the ANN.

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 with the help of ANN. 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. As a result, we can conclude that this method of order patterns based on Markov property can also be utilised to discover limited time dynamics in biomedical data as well as could be most efficient in diagnosing pathological conditions that likely identified as of theParkinso patients, the degree of interactions between captured data from two physically different systems, such as ECG as well as heart rate variation, breathing movements as well as EMG, or between various EEG channels..

References:

[1] A. Pikovsky, M. Rosenblum and J. Kurths, Synchronization- A Universal Concept in Nonlinear Sciences, Cambridge University Press, Cambridge, England, (2001).
[2] C. Schafer, M.G. Rosenblum, J. Kurths, and H. H. Abel, Intermittent Lag Synchronization In a Driven System of Coupled Oscillators, Nature (London) 392, 239 (1998).
[3] C. Schafer, M. G. Rosenblum, H. H. Abel, and J. Kurths, Synchronization in the human cardio respiratory system, Phys. Rev. E 60, 857 (1999).
[4] A. Stefanovska, H. Haken, P. V. E. McClintock, M. Hozic ,F. Bajrovic, and S. Ribaric, Reversible Transitions between Synchronization States of the Cardio respiratory System Phys. Rev. Lett.85, 4831(2000).
[5] B. Musizza, A. Stefanovska, P.V. E. McClintock,M. Palus, J. Petrovci, S. Ribaric, and F. F. Bajrovic, Interactions between cardiac, respiratory and EEG-δ oscillations in rats during anesthesia, J. Physiol. 580, 315 (2007).
[6] S. J. Schiff, P. So, T. Chang, R. E. Burke, and T. Sauer, Detecting dynamical interdependence and generalized synchrony through mutual prediction in a neural ensemble, Phys. Rev. E 54, 6708 (1996).
[7] M. L. van Quyen, J. Martinerie, C. Adam, and F. J. Varela, Nonlinear analyses of interictal EEG map the brain interdependences in human focal epilepsy, Physica (Amsterdam) 127D, 25(1999).
[8] P. Tass, M. G. Rosenblum, J. Weule, J. Kurths, A.

Pikovsky, J. Volkmann, A. Schnitzler, and H.J.Freund, Detection of n:m Phase Locking from Noisy Data: Application to Magnetoencephalography, Phys. Rev. Lett.81, 3291(1998).
[9] M. Palus, V. Komarek, Z. Hrncır, and K. Sterbova, Synchronization as adjustment of information rates: Detection from bivariate time series, Phys. Rev. E63, 046211 (2001).
[10] M. Palus, V. Komarek, Z. Prochazka, Z. Hrncir, and K. Sterbova, Synchronization and Information flow in EEGs of Epileptic Patients, IEEE Eng. Med. Biol. Mag. 20, 65 (2001).
[11] C. Bandt and B. Pompe, Permutation entropy ¬¬- a natural complexity measure for time series, Phys. Rev. Lett.88, 174102 (2002).
[12] H. Kantz, J. Kurths, and G. Mayer Kress, Nonlinear Analysis of Physiological Data, (Springer-Verlag, Berlin, 1999).
[13] H. Kantz, Nonlinear Analysis of Physiological Data, (Springer, Berlin, 1996).
[14] J. P. Eckmann and D. Ruelle, Ergodic theory of chaos and strange attractors, Rev. Mod. Phys. 57, 617 (1985).
[15] Ya. B. Pesin, Dimension Theory in Dynamical Systems, (University of Chicago Press, Chicago, 1998).(University of Chicago Press, Chicago, 1998).
[16] P. Grassberger and I. Procaccia, Estimation of the Kolmogorov entropy from a chaotic signal, Phys. Rev. A 28, 2591(1983).
[17] M. Ding, C. Grebogi, E. Ott, T. Sauer, and J.A. Yorke, Plateau Onset for Correlation Dimension: When Does it Occur?, Phys. Rev. Lett. 70, 3872 (1993) .