Application of Recurrence Quantification Analysis to EEG Signals.

Article *in* International Journal of Computers and Their Applications · January 2002

Source: DBLP

Journal Title: International journal of computers and their applications ; a publication of ISCA, International Society for Computers and Their Applications.
Vol: 9
No:
Month/Year: /2002
Pages: 1-6

Article: Thomasson, N
Author: Application of recurrence quantification

Patron: Webber, C
Borrower: INTERLIBRARY LOANq
OCLC SYMBOL: JFU
INTERLIBRARY LOAN
LOYOLA HEALTH SCIENCES LIBRARY
2160 SOUTH FIRST AVE.
MAYWOOD, IL 60153

ILLiad TN#: 593471

Please Initial Each Step:
Pull:
Update ILLiad:
Scan:
Mailed:

FAX: 708 216-8115
Copy Method: E-MAIL

☐ Not On Shelf ☐ Not As Cited ☐ Not Enough Information ☐ Exceeds Copy Limits
Please briefly describe the problem and initial:

Application of Recurrence Quantification Analysis to EEG Signals

Nitza Thomasson*
Rush-Presbyterian-Saint Luke's Medical Center, Chicago, IL 60612 USA

Charles L. Webber Jr.†
Loyola University Chicago, Stritch School of Medicine, Maywood, IL 60153 USA

Joseph P. Zbilut*
Rush-Presbyterian-Saint Luke's Medical Center Chicago, IL 60612 USA

Abstract

Numerous techniques have been applied to analyze electroencephalogram (EEG) dynamics. However, the nonstationarity of EEG signals makes it difficult to obtain reliable results. Most often, these techniques include Fast Fourier Transforms (FFTs) and wavelets, which are based on linear systems theory. An alternative method, not constrained by stationarity, namely, recurrence quantification analysis (RQA), was thus examined in its ability to reveal dynamical change in epileptic EEG signals.

Key Words: Recurrence quantification analysis, EEG, nonstationarity, signal processing.

1 Introduction

EEG signals can be considered as time series of wave-like voltage fluctuations generated by a large number of neurons. In this way, they have been analyzed using a wide range of time series analysis techniques [16]. Generally speaking, these techniques fall within two categories: linear and nonlinear methods.

Linear methods, such as power spectrum or frequency coherence, have been the traditional signal processing methods used in EEG analysis to search for brain rhythms [4, 11, 17]. Among them, the most widely used method for frequency analysis of EEG signals is the Fast Fourier Transform (FFT). The method itself transforms a time series by decomposing it into a series of sin/cosin functions [5]. Moreover, the FFT cannot properly separate periodic components of a signal when frequency bands are overlapping [6, 14]. The main disadvantage when applying linear methods to EEG signals is that they are insensitive to the nonlinear structure contained in the signals.

As a result, in the last decade attention has been focused on the development of nonlinear tools, since several researchers have provided evidence that the EEG is a nonlinear signal with deterministic properties [8, 11, 13]. Chaos-related tools such as the correlation dimension, Lypunov exponent or Kolmogorov entropy, have thus been used to characterize EEG dynamics, but with contradictory results. Indeed, while some studies reported chaotic properties in EEG segments [2-4; 10; 15; 22], others claimed an absence of the signature of low-dimensional chaos in EEG signals [20-21; 23-25]. The import of these studies suggests it is questionable to consider the brain as a low dimensional nonlinear dynamical system. In fact, Gribkov and Gribkova [9] recently reported evidence of high dimensional nonlinear dynamics in quasi-stationary EEG segments.

A major point is that real world dynamical processes and EEG signals, in particular, are nonstationary, and this restricts the possibility of dynamics extraction from the corresponding time series. In others words, in absence of stationary signals dynamical invariants (correlation dimension, Lyapunov exponents, entropies) and stationary statistical characteristics of the process (mean and standard deviation) are not very meaningful.

Consequently, analysis of EEG signals using a method that is not constrained by stationarity requirements, could bring insight into EEG dynamics. This paper presents such a method, Recurrence Quantification Analysis (RQA) as applied to EEG signals.

2 Recurrence Quantification Analysis

In 1987, Eckman et al., introduced the Recurrence Plots (RP) technique to visually analyze nonstationarity in complex systems [7]. Indeed, an RP allows one to visualize the dependence in time of orbits $\vec{x}_i$ in phase space. Knowing that the existence of a state recurrence is a fundamental property of deterministic systems [1, 19], an RP thus represents recurrences of phase space trajectory for specific states.

The construction of an RP relies upon the calculation of a $N \times N$ matrix:

$$R_{i,j} = \theta(r - \| \vec{x}_i - \vec{x}_j \|) \quad \text{for } i,j = 1 \ldots N$$

where r is a predetermined radius; $\| \vec{x}_i - \vec{x}_j \|$ the Euclidean norm of vector x_i and x_j ; θ the Heaviside function. Then, a

* Department of Molecular Biophysics and Physiology, 1653, W. Congress. E-mail: jzbilut@rush.edu.
† Department of Physiology, 2160, S. First Ave.

black pixel is drawn in the plot only if $\| \bar{x}_i - \bar{x}_j \| < r$, i.e., if they are recurrent points.

The main advantage of such a graph is that it reveals the nonstationarity of a system as well as structures characterizing specific dynamical behaviors. Stationary systems will give homogenous RPs (Figure 1), while nonstationary ones will depict brightened heterogeneous areas, revealing changes in the distribution of recurrent points (Figure 2). Furthermore, line segments parallel to the main diagonal indicate points that are close to each other successively forward in time (Figure 2). This phenomenon would not occur in random processes and points out deterministic ones. In addition, parallel diagonals formed by recurrent points at a regular distance between them depict periodic processes (Figure 1). Finally, a paling of the RP away from the main diagonal to the corners reveals a drift in the system.

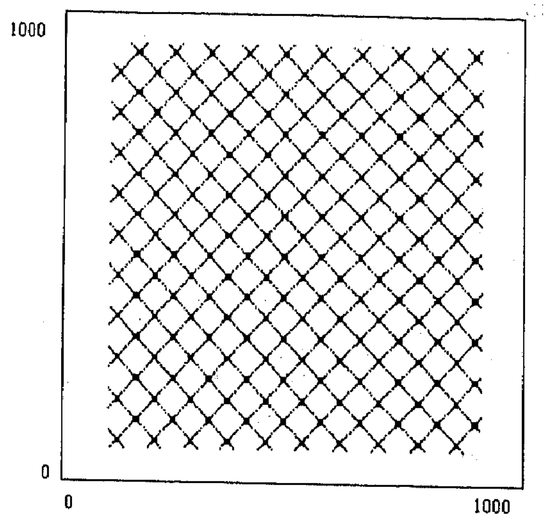

Figure 1: Illustration of a RP for a 1-Hz sine wave. The main diagonal goes from the lower left corner to the upper right one. Note the repetition of the same structure through the plot (revealing the periodicity of the signal), and its homogeneity, characteristic of stationary signals.

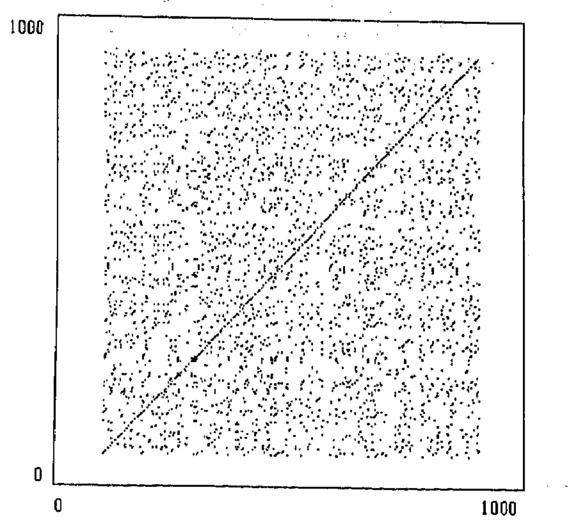

Figure 2: Illustration of a RP for the logistic equation in the chaotic regime. The main diagonal is drawn. Note the non-homogeneous aspect of the plot. Diagonal line segments of varying length are indicative of deterministic dynamics.

However, all these graphical features remain qualitative. In order to obtain quantitative measures, RQA was developed [27, 29] and applied to a wide range of physical and biological research [12, 18, 30]. Furthermore, RQA has also proved its ability to deal with noisy or short data sets [32-33] and to detect bifurcation sequences [27].

Quantitative measures of RP are defined from recurrent points density (percent recurrence); from diagonal segments parallel to the main diagonal (percent determinism); and from the length of the line and paling in the RP (maxline, entropy and trend). Moreover, in order to follow the changes of these variables in time, their computation is done for small windows moving along the time series. Then, for an N point long series $(s_1, s_2, \ldots, s_N)$, the windowed version of RQA will provide

$$
\begin{aligned}
E_1 &= (s_1, s_2, \ldots, s_N) \\
E_2 &= (s_{1+w}, s_{2+w}, \ldots, s_{N+w}) \\
E_3 &= (s_{1+2w}, s_{2+2w}, \ldots, s_{N+2w}) \\
&\ldots \\
E_p &= (s_{1+(p-1)w}, s_{2+(p-1)w}, \ldots, s_{N+(p-1)w})
\end{aligned}
$$

where w is the offset and E_p the number of epochs (windows) that satisfies the relation, $N + (p-1)w \leq n$.

Hence, quantification of recurrences [29-31] leads to the generation of five variables including: percent of recurrences (percent of plot filled with recurrent points, %REC), percent determinism (percent of recurrent points forming diagonal lines, with a minimum of two adjacent points away from the central diagonal, %DET); entropy (Shannon information entropy of the line length distribution, ENT); maxline the length of the largest line segment (measure of the system divergence, the reciprocal of which is an approximation of the largest positive Lyapunov exponent, MAXLINE); and trend (measure of the paling of recurrent points away from the central diagonal, TREND).

3 Application to Epileptic EEG Segments

1) EEG acquisition

   Epileptic EEG time series were recorded on 20 AgCl EEG electrodes positioned according to the international 10-20 system. The data were band-pass filtered (1-70 Hz) and digitally stored with a sampling frequency of 200 Hz.

2) RQA

   Prior to analysis, a careful visual inspection of the 20 recording electrodes indicated the events that occurred during 90 seconds (18000 digitized points) of epileptic EEG data (Figure 3). Namely, (a) a change in the EEG

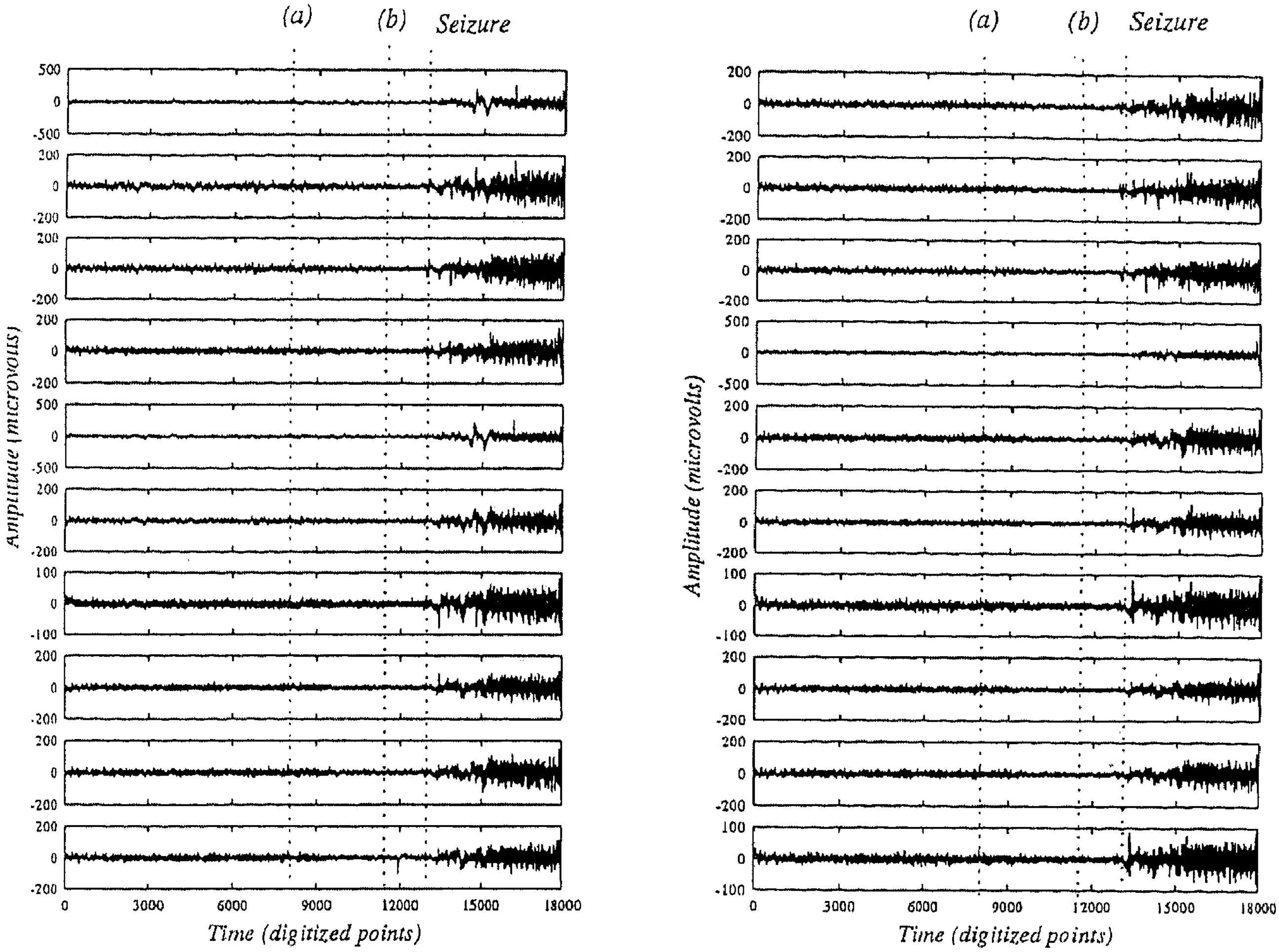

Figure 3: Twenty-lead EEG signals. Time is indicated in the x-axis (second); amplitude in y-axis (microvolt). Chronological events occurring with times are indicated: (a) change in background EEG activity, (b) widespread electromyogram, seizure onset.

background activity due to eye-blinking is noted at 40 sec, and (b) a widespread electromyogram activity probably contaminates brain electrical recording at 57 sec. Finally, the onset of the seizure occurs at around 65 sec. Such events may provoke changes in EEG dynamics that are depicted in an RP and quantitatively detected by RQA.

RP and RQA were performed on the time series obtained from the Euclidean norm of the 20 electrodes (Figure 4), defined by $\sqrt{\sum_{i=1}^{20} |x_i|^2}$ where $\bar{x}_i$ represents a vector of the successive EEG value for each lead.

The corresponding RP is represented in Figure 5. The plot is symmetrical with the main diagonal going from the left lower corner to the right upper corner. The nonstationarity of the data is salient; the plot is non-homogeneous, the repetition of a same structure through the plot does not occur, as opposed to a stationary process (cf. Figure 1). Moreover, the RP reveals specifics features. For example, the black part to the right of the x-axis corresponds to the ictal period (Figure 5 *Seizure*). But changes in dynamics also seem to occur at approximately the center of the x-axis (Figure 5a), as well as later, where vertical black lines are becoming closer to each other (Figure 5b).

As previously pointed out, an RP allows a visual and a qualitative inspection of the changes in EEG dynamics. To confirm the observations, RQA was performed using an Euclidean norm for distance calculation (re-scaled on unit interval); a radius r of 5 to define the recurrences; and line segments parallel to the main diagonal were counted if composed of two or more points.

Results in the computation of RQA variables are illustrated in Figure 6. The first 65 seconds constitute the preictal period, followed by the seizure. The evolution of the five RQA variables (%REC, %DET, ENT, MAXLINE, TREND) with time exhibits major transients. Significance of these changes was determined using a running 500 ms window overlapping one point at a time to calculate a 99 percent confidence interval. This precaution thus singled out major transients in the dynamics. Such changes are found to be simultaneous in

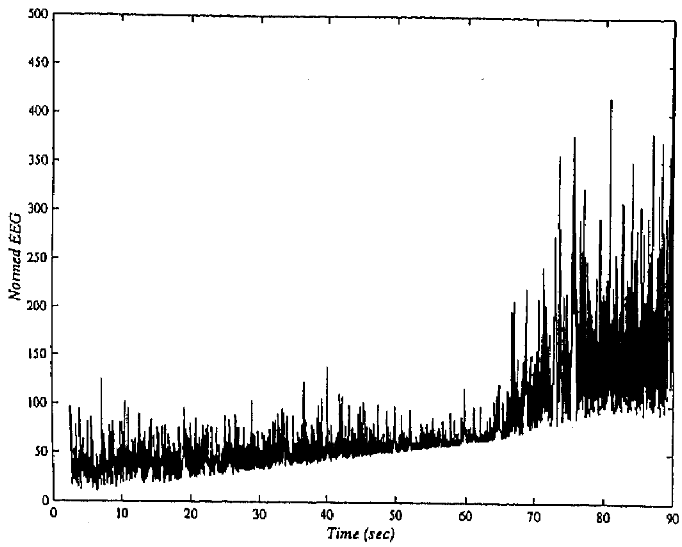

Figure 4: Sample of a normed epileptic EEG segment obtained by taking the Euclidean norm of the 20 recording electrodes. Time is given in the x-axis (sec); amplitude in y-axis (microvolt).

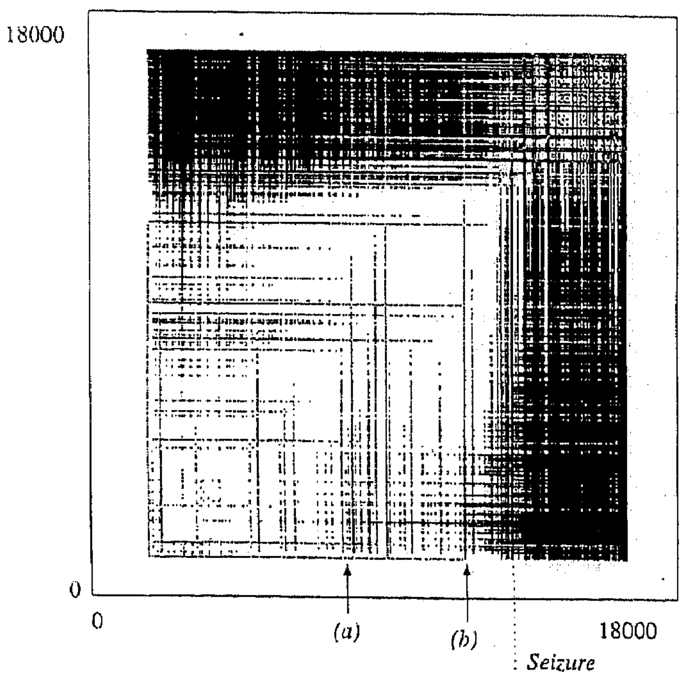

Figure 5: Representation of the RP of a 90 seconds normed epileptic EEG segment. Seizure onset is indicated by the dotted line; it clearly marks a change in dynamics. Other transients are observed in (a) where a few vertical black lines appear and in (b) where they become more numerous and close to each other as the seizure onset approaches.

the different RQA variables, and are concordant with the features observed in the RP. Indeed, a change in dynamics characterized by a drop in %REC, %DET, ENT and MAXLINE occurs at 40 seconds (Figure 6(a)). This change is associated with a modification of EEG background activity due to eye-blinking. Moreover, a transient towards high values of RQA variables (except in the case of TREND where the relationship is reciprocal) is observed at 57 seconds, followed by others at 63 and 64 seconds (Figure 6(b)). This unstable state may reflect a transitional dynamic related to widespread electromyogram activity; a progressive "route" toward the seizure where abnormally discharging neurons act as pacemakers to recruit and entrain other normal neurons. Finally, the significant decrease in the variables observed at 65 seconds indicates the seizure onset (Figure 6). This study shows that RQA may be a sensitive diagnostic measure of pathologic changes in EEGs.

4 Conclusion

The aim of this paper was to present the ability of RQA to reveal dynamical changes in EEG signals. Without requiring the signal to be stationary, RQA appears to be an appropriate tool in the analysis of brain electrical activity. Developed from the recurrence plot technique [7], RQA provides quantitative measures of system dynamics and is able to reveal transients in the data set [27-29]. Applied to epileptic EEGs it demonstrated transients occurring prior to seizures [26]. RQA may thus be a promising approach in the characterization of brain states, such as neuropathology or cognitive activity. Nevertheless, this study is preliminary and additional trials are necessary to determine the method's utility.

Acknowledgment

Nitza Thomasson's work has been supported by INSERM, France.

References

[1] J. H. Argyris, G. Faust, and M. Haase, "An Exploration of Chaos," North Holland, Amsterdam, 1994.

[2] A. Babloyantz and A. Destexhe, "Low Dimensional Chaos in an Instance of Epilepsy," *Proc. Natl. Acad. Sci.*, USA, 83:3513-3517, 1986.

[3] M. C. Casdagli, L. D. Iasemidis, J. C. Sackellares, S. N. Roper, R. L. Gilmore, and R. S. Savit, "Characterizing Nonlinearity in Invasive EEG Recordings from Temporal Lobe Epilepsy," *Physica D.*, 99:381-399, 1996

[4] M. C. Casdagli, L. D. Iasemidis, R. S. Savit, R. L. Gilmore, S. N. Roper, and J. C. Sackellares, "Nonlinearity in Invasive EEG Recordings from Temporal Lobe Epilepsy," *Electroenceph. Clin. Neurophysiol.*, 102:98-105, 1997.

[5] R. E. Challis and R. I. Kidney, "Biomedical Signal Processing (in Four Parts), Part 3: The Power Spectrum and Cohenrence Function," *Med. and Biol. Eng and Comput.*, 29:225-241, 1991.

[6] R. Draganova, "The Method of Linear Transformation in Revealing EEG Polyharmonic Components in Comparison to the Fourier Analysis," *Medical Engineering & Physics*, 21:9-14, 1999.

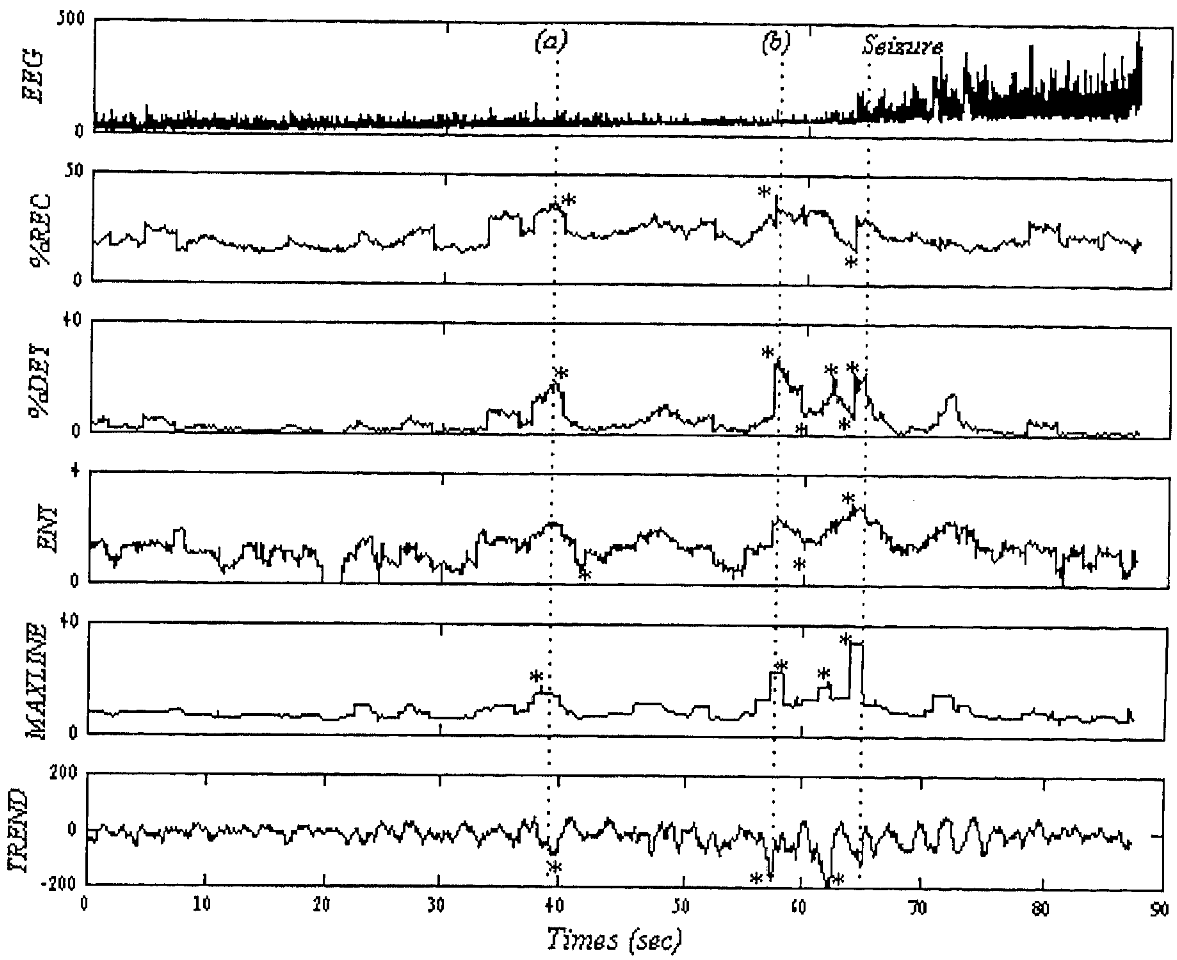

Figure 6: Results of the windowed RQA for Figure 4. Variations of the five RQA variables are depicted: %REC, %DET, ENT, MAXLINE, TREND. Dotted lines indicate main changes in dynamics related to RP features and electrophysiological event descriptions. (a) A drop in values of RQA variables (except TREND where it is reciprocal) is observed. This change is related to background EEG activity resulting from eye-blinking. (b) A general increase in RQA values is observed with many significant transients (denoted by stars). The ictal period is indicated by "Seizure", and corresponds to a decrease toward small values of RQA variables.

[7] J. P. Eckman, S. O. Kamphorst, and D. Ruelle, "Recurrence Plots of Dynamical Systems," *Europhys. Lett.*, 4:973-977, 1987.

[8] T. Elbert, W. J. Ray, J. Kowalik, J. E. Skinner, K. E. Graf, and N. Birbaumer, "Chaos and Physiology: Deterministic Chaos in Excitable Cell Assemblies," *Physiol. Rev.*, 74:1-47, 1994.

[9] D. Gribkov and V. Gribkova, "Learning from Nonstationary Time Series: Analysis of Electroencephalograms," *Phys. Rev. E.*, 61(6):6538-6545, 2000.

[10] L. D. Iasemidis and J. C. Sackellares, "Chaos Theory in Epilepsy," *The Neuroscientist*, 2:118-126, 1996.

[11] L. D. Iasemidis, J. C. Principe, and J. C. Sackellares, *Nonlinear Signal Processing in Medicine*, ed. M. Akay, IEEE Press, 1999.

[12] S. Ikegawa, M. Shinohara, T. Fukunaga, J. P. Zbilut, and C. L. Webber, "Nonlinear Time-Course of Lumbar Muscle Fatigue Using Recurrence Quantification," *Biol. Cyber.*, 82:373-382, 2000.

[13] B. H. Jansen, "Is It and So What? A Critical Review of EEG-Chaos," In: *Measuring Chaos in the Human Brain*, Eds. D. W. Duke and W. S. Pritchard, World Scientific, Singapore, pp. 83-96, 1991.

[14] E. Juegens and F. Roesler, "How do Alpha Oscillations Influence Gamma Band Activity?" *Psycholoquy*, 95.6.09.brain-rhythms.10.juengens, 1995.

[15] K. Lehnertz and C. E. Elger, "Spatiotemporal Dynamics of the Primary Epileptogenic Area in Temporal Lobe Epilepsy Characterized by Neuronal Complexity Loss," *Electroenceph. Clin. Neurophysiol.*, 95:108-117, 1995.

[16] F. Lopes da Silva, "EEG Analysis: Theory and Practice;

Computer-Assisted EEG Diagnosis: Pattern Recognition Techniques," In: *Electroencephalography; Basic Principles, Clinical Applications and Related Fields*, Eds. E. Niedermeyer and F Lopes da Silva, Urban & Schwarzenburg, Baltimore, pp. 871-919, 1987.

[17] F. Lopes da Silva, *Electroencephalography*, Eds. E. Niedermeyer and F Lopes da Silva, Williams and Wilkins, Baltimore, 1993.

[18] C. Manetti, M. A. Ceruso, A. Giuliani, C. L. Webber, and J. P. Zbilut, "Recurrence Quantification Analysis as a Tool for the Characterization of Molecular Dynamics Simulation," *Phys. Rev. E*, 59:992-998,1999.

[19] E. Ott, *Chaos in Dynamical Systems*, University Press, Cambridge, 1993.

[20] M. Paluš, "Nonlinearity in Normal Human EEG: Cycles, Temporal Asymmetry, Nonstationarity and Randomness, but not Chaos," *Biol. Cyber.*, 75:389-396, 1996.

[21] M. Paluš, "Nonlinear Dynamics in the EEG Analysis Disappointments and Perspectives," In: *Nonlinear Dynamics and Brain Functioning*, eds. N. Pradhan, P. Rapp, and R. Sreenivasan, Novasicence, New York, USA, 1999.

[22] W. S. Pritchard, D. W. Duke, K. L. Coburn, N. C. Moore, K. A. Tucker, M. W. Jann, and R. M. Hostetler, "EEG Based, Neural-Net Predictive Classification of Alzheimer's Disease Versus Control Subjects is Augmented by Nonlinear Measures," *Electroencephalogr. Clin. Neurophysiol.*, 91(2):118-130, 1994.

[23] S. A. R. B. Rombouts, R. W. M. Keunen, and C. J. Stam, "Investigation of Nonlinear Structure in Multichannel EEG," *Phys.Lett. A*, 202:352-358, 1995.

[24] J. Theiler, "Spurious Dimension from Correlation Algorithms Applied to Limited Times-Series Data," *Phys. Rev. A*, 34:2427-2433, 1986.

[25] J. Theiler and P. E. Rapp, "Re-Examination of the Evidence for Low-Dimensional Nonlinear Structure in the Human Electroencephalogram," *EEG Clin. Neurophysiol.*, 98:213-222, 1996.

[26] N. Thomasson, T. J Hoeppner, C. L. Webber, Jr., and J. P. Zbilut, "Nonlinear Seizure Prediction by Surface EEGs," *Epilepsia*, 41(suppl. 7):102-103, 2000.

[27] L. L. Trulla, A. Giuliani, J. P. Zbilut, and C. L. Webber, "Recurrent Quantification Analysis of the Logistic Equation with Transients," *Phys. Lett. A*, 223:225-260, 1996.

[28] B. Weber, K. Lehnertz, C. E. Elger, and H. G. Wieser, "Neuronal Complexity Loss in Interictal EEG Recorded with Foramen Ovale Electrodes Predicts Side of Primary Epileptogenic Area in Temporal Epilepsy: a Replication Study," *Epilepsia*, 39:922-927, 1998.

[29] C. L. Webber, Jr. and J. P. Zbilut, "Dynamical Assessment of Physiological Systems and States using Recurrence Plot Strategies," *J. Appl. Physiol.*, 76:965-973, 1994.

[30] C. L. Webber, Jr. and J. P. Zbilut, "Assessing Deterministic Structures in Physiological Systems using Recurrence Plot Strategies," In: *Bioengineering Approaches to Pulmonary Physiology and Medicine*, Ed.M.C.K. Khoo, Plenum Press, N Y, Chapter 8, pp.137-148, 1996.

[31] J. P. Zbilut and C. L. Webber, "Embeddings and Delays as Derived from Quantification of Recurrence Plots," *Phys. Lett. A*, 171:199-203, 1992.

[32] J. P. Zbilut, A. Giuliani, and C. L. Webber, "Detecting Deterministic Signals in Exceptionally Noisy Environments using Cross Recurrence Quantification," *Phys. Lett. A*, 246:122-128, 1998.

[33] J. P. Zbilut, A. Giuliani, and C. L. Webber, Jr., "Recurrence Quantification Analysis and Principle Component in the Detection of Short Complex Signals," *Phys. Lett. A*. 237:131-135, 1998.

Nitza Thomasson was born in 1973 in Blois, France. She received her Ph.D in Cognitive Sciences (1999) from the University of Paris VI- EHESS. She is currently a post-doctoral fellow with sponsorship from INSERM (France) at Rush Medical Center, Chicago. Her research interests include EEG nonlinear analysis in neurology and psychiatry.

Charles L. Webber, Jr. is a Professor of Physiology at Loyola University, Chicago where he received his Ph.D. in Systems Physiology. For two years he was a postdoctoral fellow of the Max Planck Society studying the neural control of breathing. Research interests include biological rhythms, proteomics and genomics. He and Joseph Zbilut are authors of *Recurrence Quantification Analysis* which has utility in multiple fields of study. He has received Teacher-of-the-Year Award five times over a quarter-century of medical teaching.

Joseph P. Zbilut (photo is not available) is currently a Professor of Molecular Biophysics and Physiology at Rush University, Chicago. He received doctorates from Loyola Univ. Chicago, and from Rush University, specializing in physiological signal processing and semiotics. With Michail Zak of the Jet Propulsion Lab, and Ron Meyers of the Army Research Lab, he co-wrote *From Instability to Intelligence: Complexity and Predictability in Nonlinear Dynamics*. He is also on the Editorial Board of the *International Journal of Computers and Their Applications*.