IDENTIFICATION OF COMPLEX PROCESSES BASED ON ANALYSIS OF PHASE SPACE STRUCTURES

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Abstract. The problem of investigation of temporal and/or spatial behavior of highly nonlinear or complex natural systems has long been of fundamental scientific interest. At the same time it is presently well understood that identification of dynamics of processes in complex natural systems, through their qualitative description and quantitative evaluation, is far from a purely academic question and has an essential practical importance. This is quite understandable as systems with complex dynamics abound in nature and examples can be found in very different areas such as medicine and biology (rhythms, physiological cycles, epidemics), atmosphere (climate and weather change), geophysics (tides, earthquakes, volcanoes, magnetic field variations), economy (financial markets behavior, exchange rates), engineering (friction, fracturing), communication (electronic networks, internet packet dynamics) etc. The past two decades of research on qualitative and especially quantitative investigations of dynamics of real processes of different origin brought significant progress in the understanding of behavior of natural processes. At the same time serious drawbacks have also been revealed. This is why exhaustive investigation of dynamical properties of complex processes for scientific, engineering or practical purposes is now recognized as one of the main scientific challenges. Much attention is paid to elaboration of appropriate methods aiming to measuring the complexity of both global and local dynamical behaviors from the observed data sets - time series. This chapter presents a short overview of modern methods of qualitative and quantitative evaluation of dynamics of complex natural processes such as calculation of Lyapunov exponents and fractal dimensions, recurrence plots and recurrence quantification analysis. Other related methods are also described. The traditional approach to studying dynamical behavior of complex nonlinear systems is to reconstruct from observation scalar time series state or phase space plot. This graph indicates how the systems behavior changes over the time. We focus on the methods of identification and quantitative evaluation of complex dynamics that are based on the testing of evolutionary and geometric properties of phase space graphs as images of investigated complex dynamics. For practical examples of the application of nonlinear methods for identification of complex natural processes, our results on medical, geophysical, hydrological, and stick-slip time series analysis are presented.

Key words: complexity, dynamics, nonlinear time series analysis, natural processes.

1. Introduction

A common statement in the scientific literature is that the complexity of nature has always been an inevitable problem in our efforts towards understanding and describing spatial forms and temporal evolution of natural systems. "Complex" and "complexity" are often heard scientific terms, though there is little consensus on their official definitions and they still have a variety of meanings depending on the context (Arecchi and Fariny, 1996; Shiner and Landsberg, 1999). This is because the study of complexity, in both a dynamical and structural sense, is in its infancy and is a rapidly developing field at the forefront of many areas of science including mathematics, physics, geophysics, economics, biology, etc. Available current scientific definitions of complexity are often so controversial that the half-serious statement that the complexity problem is itself complex (Yao and Davison, 2004) looks quite reasonable. In spite of this, it is clear that natural systems and/or processes are complex due to their nonlinearity, an intrinsic property of the underlying laws conditioning absence of strict determinism of the universe. The presence of this property is revealed in the specificity of systems' temporal behavior and spatial structures, what we name as complex (Kantz and Schreiber, 1997; Matcharashvili and Javakhishvili, 2000). In order to avoid misunderstanding caused by tradition, associating the term nonlinearity exceptionally with dynamics, it should be stressed that at present the terms nonlinearity and complexity commonly are regarded as synonyms. This is convenient in order to address both complex nonlinear temporal evolution and complex non-Euclidean spatial forms of natural systems. As an inherent property, nonlinearity or complexity is revealed in the absence of a deterministic cause-effect relation, observed on different spatial and temporal scales. This property incorporates phenomena with a very broad diversity of dynamical features. Generally this diversity manifests itself in a certain kind of hierarchy of dynamical behavior ranging from strict determinism to total randomness. Most important is that between these extremes there are many intermediate states that reveal different degrees of orderliness such as, e.g., periodicity, quasiperiodicity, deterministic chaos, low and high dimensional dynamics, hyperchaos, etc. (Kantz and Schreiber, 1997; Theiler and Prichard,). Until recently both qualitative detection and quantitative evaluation of these intermediate states was impossible due to the absence of a corresponding mathematical formalism and appropriate data analysis methods. It is necessary to mention that traditional linear methods mostly are not effective for complex processes of interest. This is why in different fields of science and practice there has been an explosion of papers searching for methods aiming at detection of peculiarities of complex systems evolution in order to achieve reliable identification of processes by their dynamics. At present a time series nonlinear analysis technique is elaborated (Abarbanel and Tsimring, 1993; Berge and Vidal, 1984; Eckman and Ruelle, 1985; Kantz and Schreiber, 1997; Packard and Shaw, 1980; Rapp and Farwell, 1993), which often (but not always due to the same cause - complexity of nature) enables us to achieve correct qualitative and quantitative assessment of complex processes by measuring their dynamical characteristics. These methods aiming to measure the complexity of both local and global spatial and temporal scales are universal and applicable to a very broad range of complicated processes. There are several main approaches to quantify the complexity of processes by analysis of measured time series (Boffetta and Vulpiani, 2002). Some of them have roots in dynamical systems and fractal theory and include Lyapunov exponents, Kolmogorov-Sinai entropy and fractal dimensions (Abarbanel and Tsimring, 1993; Eckman and Ruelle, 1985; Kantz and Schreiber, 1997). These methods are based on reconstruction and testing of phase space objects that are equivalent to unknown dynamics. The other methods stem from information theory including Shannon entropy (Schreiber, 1993), algorithmic complexity (Shiner and Landsberg, 1999; Yao and Davison, 2004) and mostly are based on symbolic dynamics. For different complex systems, various approaches to complexity measurements can be used. The common problem of many methods, including ones based on phase space reconstruction, is the requirement of long high quality stationary data sets, which is not always easy to fulfill when dealing with natural or laboratory systems. To overcome these difficulties new phase space structure testing measures have been proposed, such as recurrence plots (RP) and recurrence quantitative analysis (RQA). These methods equip us to gain new understanding of complex natural dynamics. At the same time it should be stressed that, notwithstanding all efforts that are obtained by different modern methods, measures of complex dynamics sometimes may be mutually complementary or may be even contradictory and should be carefully tested.

2. Phase space structures as image of dynamics

As it was mentioned above here we focus on complex dynamics investigation methods based on phase space structure testing. The practical method to reconstruct the equivalent to real complex dynamics structure from the time series of a single observable was invented by Packard et al., (1980) and Takens, (1981). Generally, the state of an investigated system can be described by its state variables $x_1(t), x_2(t), ..., x_d(t)$. These state variables form a vector $\vec{x}(t)$ in a d-dimensional phase space. The rotation of $\vec{x}(t)$ forms phase space trajectores or orbits. When the system of interest is nonrandom it has a property known as recurrence (Ruelle, 1994). This means that after some transients, the system comes back close to the some points in the phase space again and again. The character of time evolution of trajectory forms a phase space structure - the attractor of the system. The shape of the attractor provides essential information on dynamical features of the investigated process. Thus the attractor in phase space can be considered as an equivalent image of dynamics under consideration. Generally a point in a phase space is associated with a single state of the system which is fully defined by a set of m dynamical variables. It is clear that, in order to have a complete description of the state of the dynamical system of interest, these m physical quantities should all be measured, at least in principle. Unfortunately, in most experimental situations, not all (and often only a single) physical quantity of a state variable can be measured; all that we have is a one-dimensional time series and from this series one would like to learn as much as possible about the system that generated the signal. As a rule measurements result in discrete time series $g_i(t)$, where $t = i\Delta(t)$ and Δt is the sampling rate. Commonly the sampling rate is constant, forming equidistant time series, but this is not always the case. Time series taken at time intervals of different length, so called unevenly sampled time series, are also quite common (Schreiber and Schmitz, 1999). So far as systems variables are coupled a single component contains essential information about the dynamics of the whole system (Castro and Sauer, 1997; Kantz and Schreiber, 1997; Rapp and Farwell, 1993). Therefore the trajectory reconstructed from this scalar time series is expected to have the same properties as the trajectory embedded in the original phase space, formed by all m state variables. Loosely speaking Packard et al., (1980) and Takens, (1981) independently proposed the idea of using a single sequence of measurements to transform process dynamics into the phase space structure (the image of investigated dynamics) to gain the information on the unknown underlying dynamics from this structure. According to the embedding theorem, there exists a one-to one image of an attractor in embedding space, if the embedding dimension is sufficiently high (Hegger and Schreiber, 1999). The idea was successfully realized after Takens, (1981) proved that it is possible to reconstruct from a single scalar time series a new attractor which is diffeomorphically equivalent to the attractor in the original state space of the system under study. Essentially two methods of reconstructions are available, delay coordinates and derivative coordinates techniques. Derivative coordinates were originally proposed by Packard et al., (1980) and consist of using the higher order derivatives of the measured time series as the independent coordinates. Since derivatives are more susceptible to noise this technique is usually not very practical for real life data, which are inherently very noisy. Therefore the method of delay coordinates was recognized as a more practical tool. Data delayed by a lag T helps to exclude distortions of analyzed dynamics caused by temporal closeness of observations. The T value should be large enough to avoid insubstantial functional dependence between data and not too large to make them be statistically completely independent. If these conditions are fulfilled, a set of d dimensional vectors in d dimensional space can be reconstructed:

$$\vec{X}(i) = [x(i), x(i+T), x(i+2T), ..., x(n+(d-1)T)]. \tag{1}$$

The Takens, (1981) theorem guarantees that the dynamics reconstructed in this way, if properly embedded, is equivalent to the dynamics of the original, underlying system (Packard and Shaw, 1980; Takens, 1981). Equivalence of these two dynamics means that their dynamical invariants (e.g. generalized dimensions, the Lyapunov spectrum, to be described below) are identical. The delay time, T, for the reconstructions can be calculated from the autocorrelation function or from the mutual information (MI) first minimum. The averaged mutual information evaluates the amount of bits of information shared between two data sets over a range of time delays and is defined as: $I(X,Y) = \sum_{i,j}^{N} p(i,j) \log_2 \frac{p(i,j)}{p_x(i)p_y(j)}$ (Abarbanel and Tsimring, 1993; M. and Thomas, 1991; Kantz and Schreiber, 1997; Kraskov and Grassberger,) , where $p_x(i)$ and $p_y(j)$ are probabilities of finding measurements $x(i)$ and $x(i+T)$ in the time series, $p(i,j)$ is the joint probability of finding measurements $x(i)$ and $x(i+T)$ in the time series, and T is the time lag. It is important to mention that in contrast to the linear correlation coefficient (which also can be used for delay time calculation), MI is also sensitive to dependencies which are not linear, i.e. do not manifest themselves in the covariance. MI is zero if and only if the two random variables are strictly independent. The MI calculation is not only used to find the correct time value delay, it is also important as a tool for providing information on the probability distribution of phase space points.

In order to define the correct value of the embedding dimension $d_e \geq 2d_a + 1$ (where d_e is the dimension of the embedding space and d_a is the attractors dimension) one uses the so-called false nearest neighbor method (Hegger and Schreiber, 1999; Kennel and Abarbanel, 1992). The percentage of false nearest neighbors (phase points projected into neighborhoods of points to which they would not belong in higher dimensions) approaches zero while the dimension of the phase space increases. Generally recurrence to certain states or phase space locations is a feature of deterministic dynamics (more generally non-random dynamics with some extent of determinism). Therefore many complex dynamics analysis statistical tools are based on the inspection of neighborhoods in a reconstructed phase space (e.g. see Casdagli, 1997). Indeed, if phase structures of two processes located in correctly embedded phase space are close then the dynamics of interest will also be close by their characteristics (of course they will not completely coincide due to dynamical instability and/or noise).

We will shortly describe several methods of phase space structure testing.

Since the attractor (phase space image of dynamics) is formed, two most popular ways for the quantitative evaluation of complexity of the analyzed dynamics are: quantification of the average evolution patterns of neighboring trajectories in a state space and/or quantification of the geometric patterns of state space object.

Evolution of phase space trajectories could be analyzed by calculation of the spectrum of Lyapunov exponents or by calculation of the maximal Lyapunov exponent $\lambda_{\max}$. Generally Lyapunov exponents quantify the average exponential rate of divergence of neighbouring trajectories in a state space, and thus provide a measure of the sensitivity of a system to local perturbations (Rosenstein and DeLuca, 1993; Kantz and Schreiber, 1997). For measured data sets the maximum Lyapunov exponent $\lambda_{\max}$ for a dynamical system can be determined from $d(t) = d_0 e^{\lambda_{\max} t}$, where $d(t)$ is the mean divergence between neighboring trajectories in a state space at time t and d_0 is the initial separation between neighboring points. There are several methods (Wolf and Vastano, 1985; Sato and Sawada, 1987; Rosenstein and DeLuca, 1993) for estimating $\lambda_{\max}$, which often suffer from serious practical drawbacks. Namely, they are unreliable for small data sets and need essential computational resources. Generally, if $\lambda < 0$ phase trajectories are drawing together and the dynamical system has an attractor in the form of a fixed point. When $\lambda = 0$, the system tends to the stable limit cycle. $\lambda > 0$ means that phase trajectories are moving away and such a system may be chaotic or random (Rosenstein and DeLuca, 1993). In order to characterize unknown dynamics by the geometry of reconstructed phase structures the algorithm for calculation of fractal dimensions of phase space point sets should be used. It is known that the fractal dimension of an attractor roughly characterizes the complexity of a system and gives a lower bound for the number of equations or variables needed for modeling the underlying dynamical process. There are several such measures based on the quantification of self similar properties of phase space objects. These measures are information dimension (d_i), Hausdorf dimension d_H, etc.(Abarbanel and Tsimring, 1993; Kantz and Schreiber, 1997). We shortly describe here only the method of computing the correlation dimension or fractal dimension as proposed by Grassberger and Procaccia, (1983)(GPA). In spite of difficulties, when applied to real data sets, GPA remains the most popular and often used method of quantifying geometrical features of phase space objects. This is probably due to the simplicity of the algorithm (Bhattacharya, 1999) and the fact that the same intermediate calculations are used to estimate both fractal dimension and entropy. The correlation sum, $C(r, N)$, quantifies the way in which the density of points in state space scales with the size of the volume containing those points. The correlation sum $C(r)$ of a set of points in a vector space is defined as the fraction of all possible pairs of points which are closer than a given distance r . The basic formula useful for practical application is

$$C(r, N) = \frac{2}{(N-w)(N-w+1)} \sum_{i=1}^{N} \sum_{j=i+w}^{N} \Theta\left(r - \|x_1 - x_j\|\right) \tag{2}$$

where $\Theta(x)$ is the Heaviside step function, $\Theta(x) = 0$ if $x < 0$ and $\Theta(x) = 0$ if $x \geq 0$; $\|x_i - x_j\|$ is the Euclidian norm ($i = j$ is excluded); w is Theiler's window. For fractal systems for long enough time series and for small r, the relationship $C(r) \propto r^{\nu}$ is correct. Ordinarily such a dependence is correct only for the restricted range of r values, the so-called scaling region. Correlation dimension ν or d_2 is defined as

$$\nu = d_2 = \lim_{r \to 0} \frac{\log C(r)}{\log(r)}. \tag{3}$$

In practice the value of d_2 is found from the slopes of $\log C(r, N) - \log r$ curves for different phase space dimensions. The correlation dimension of an unknown process is the saturation value of d_2, which does not change with increasing phase space dimension. If saturation does not take place the correlation dimension is infinitely large, which is typical for random processes.

For a correct analysis it is necessary to have long enough data sequences, at least $N \geq 10^{d/2}$, where N is the length of the time series and d is the dimension of the attractor (Abarbanel and Tsimring, 1993). The three dimensions above satisfy the relation $d_2 < d_i < d_H$, with equality when the points in the state space are distributed uniformly over the attractor. In spite of the popularity of the d_2 calculation method, GPA results must be interpreted with great care as it is well known that linear stochastic processes can also mimic low-dimensional dynamics (Rapp and Farwell, 1993; Theiler and Prichard,). In other words, the saturation of a correlation dimension and the existence of positive Lyapunov exponents cannot always be considered as decisive proof of deterministic chaos, a dynamical regime which is predictable in the sense of patterns, and is closest to quasiperiodicity (Kantz and Schreiber, 1997; Rapp and Farwell, 1993). Since linear correlations lead to many spurious conclusions in nonlinear time series analyses, it is important to verify results obtained using the so-called surrogate data approach. This is a method to test the null hypothesis that the analyzed time series is generated by a specific process with known linear properties (Theiler and Farmer, 1992). It should be stressed again that the above phase space measures have strict restrictions in the sense of time series length and are mostly relevant for the analysis of low dimensional or deterministically chaotic systems. When the dynamics of the investigated process is more complex or when the dimension of the underlying attractor is moderately large, say $d_2 > 5$, results of dimensional analysis on a finite amount of real data series are not reliable enough (Schreiber and Schmitz, 1999). Moreover the real data series are often very noisy and contain measurement noise as well as dynamical noise (noise interacting with dynamics); then the conventional estimates fail as well. Therefore when we deal with complex dynamics, a less ambitious and more realistic goal commonly is to search for the inherent nonlinearity of the processes, or to rank them by the extent of nonlinearity. The practical importance of this statement becomes clear in the light of known facts that in most cases the dynamical behavior of natural scale-invariant processes is non-random, revealing nonlinear structure. Very seldom is there some evidence of a deterministic chaotic type of dynamics (C., 1998; Marzochi, 1996; Theiler and Prichard,). The mentioned method of surrogate data equips us for testing the nonlinear structure of complex dynamics. Indeed, the concept of surrogates was introduced (Theiler and Farmer, 1992) in order to detect nonlinearity in time series. The surrogate data is inherently a stochastic signal which mimics certain statistical properties of the original signal, such as temporal autocorrelation and Fourier power spectra. The surrogates can be constructed from the original time series on the basis of different null hypotheses. The three types of surrogates used most often address the three main hypotheses, namely, temporally independent noise, linearly filtered noise, and nonlinear transformation of linear filtered noise. So whenever we try to quantify the degree of nonlinearity, the results of calculating the above measures should be compared with the similar quantities for surrogate data sets. Phase randomized surrogate sets (PR - obtained by destroying the nonlinear structure through randomization of the phases of a Fourier transform of the original time series and the following inverse transformation) is often used to test the null hypothesis that the time series are linearly correlated with Gaussian noise (Theiler and Farmer, 1992). Also the Gaussian scaled random phase (GSRP) surrogate set can be generated to address a null hypothesis that the original time series is linearly correlated noise that has been transformed by a static, monotone nonlinearity (Rapp and Jumenez-Montero, 1994; Rapp and Farwell, 1993). GSRP surrogates are generated in a three-step procedure. At first a Gaussian set of random numbers is generated, which has the same rank structure as the original time series. After phase randomized surrogates of these Gaussian sets are constructed. Finally the rank structure of the original time series must be reordered according to the rank structure of the phase randomized Gaussian set (Theiler and Farmer, 1992). Generally these two methods of generation of surrogates are based on shuffling of the original data set but, in the case of Gaussian scaled random phase surrogates, controlled shuffles (Rapp and Jumenez-Montero, 1994) can give more precise and reliable results than the unstructured shuffles of the random phase surrogates.

Commonly, for testing the null hypothesis, d_2 is used as the discriminating metric. There are several ways to measure the difference between the discriminating metric measure of the original (M_{orig}) and the surrogate (M_{surr}) time series. The most common measure of the significance of the difference between the original time series and the surrogate data is given by the criterion $S = |\langle M_{surr}\rangle - M_{orig}| / \sigma_{surr}$, where σ_{surr} denotes the standard deviation of M_{surr} . The details of the procedure, as well as an analytic expression for ΔS - the uncertainty in S, are described in (Theiler and Farmer, 1992). Alternatively, Monte Carlo probability can be used, defined as P_M = (*number of cases* $M \leq M_{orig}$)/(*number of cases*), where P_M is an empirical measure of the probability that a value of M_{surr} will be less than M_{orig}. It is particularly appropriate when the number of surrogates is small, or when the distribution of values of M obtained with surrogates is non-Gaussian (Rapp and Jumenez-Montero, 1994). For rejecting the null hypothesis, the Barnard and Hope nonparametric test (Rapp and Farwell, 1993) can be used. With this criterion, the null hypothesis is rejected at a confidence level $p_c = 1/(N_{surr} + 1)$, if $M_{orig} < M_{surr}$ for all surrogates. One serious real data analysis problem is the influence of noise. One often uses the so-called nonlinear noise reduction method (which in fact is phase space nonlinear filtering) instead of common linear filtering procedures. The latter, as is well known, may destroy the original nonlinear structure of analyzed complex processes (Hegger and Schreiber, 1999). Nonlinear noise reduction relies on exploration of the reconstructed phase space of the considered dynamical process instead of using frequency information of linear filters (Hegger and Schreiber, 1999; Kantz and Schreiber, 1997; Schreiber, 1999). As pointed out above, most methods of analysis need rather long and stationary data sets, which is commonly not typical for measured time series. This limitation gave a strong impetus to further development of new techniques to get an insight into the complex processes having relatively short and noisy observable time series. For this purpose several measures of complexity, mostly based on a symbolic dynamics approach, have been proposed. These include Renyi entropies, effective complexity, ε complexity etc. (Rapp and Jimenez-Montano, 2001; Wackerbauer and Scheingraber, 1994). Here we will not discuss all these methods but focus on the approach based on the study of attractors organization (or testing of topology of phase space images of unknown dynamics). This relatively new technique, oriented on the exploration of the phase space structure-image of dynamics, is the method of recurrence plots (RP) (Marwan, 2003). Let us recall here that if a dynamical system under investigation has any deterministic structure, an attractor appears in state space. As was already mentioned, an attractor is the set of points in phase space towards which dynamical trajectories will converge. Again, recurrence is a fundamental property of nonrandom dynamical systems, which exponentially diverge under small disturbances although, after some time, return to a state that is arbitrarily close to a former state. Recurrence plots visualize such a recurrent behavior of dynamical system. Usually real processes are characterized by complex dynamics embedded in a high dimensional phase space. RP enables to investigate the structure of these high dimensional phase spaces through a two-dimensional representation of their recurrences. It is important to observe that the recurrence plot method is effective for even nonstationary and rather short time series (Gilmore, 1993; Gilmore, 1998).Generally recurrence plots are designed to locate hidden recurring patterns and structure in time series and are defined by the $N \times N$ symmetric matrix:

$$R_{i,j} = \Theta(\varepsilon_i - \left\| \vec{x}_i - \vec{x}_j \right\|), \qquad i,j = 1, ..., N, \tag{4}$$

where $\vec{x}_{i,j}$ are reconstructed phase space vectors, using Taken's time delay method. Insofar as RP is based on Takens delay-coordinate embedding, the dynamical invariants of the true and reconstructed dynamics are identical when that embedding is correctly chosen. Therefore it is natural to assume that the RP of a correctly reconstructed trajectory bears similarity to an RP of the true dynamics. In fact in (4) $\vec{x}_i$ stands for the point in phase space at which the system is situated at time i, ε_i is a predefined cut-off distance and $\Theta(x)$ is the Heaviside function. The cut-off distance defines a sphere centered at $\vec{x}_i$. Recurrence of the phase space trajectory to a certain state is a fundamental property of deterministic dynamical systems (Argyris and Haase, 1994; Marwan and Kurths, 2002). If the trajectory in the reconstructed phase space returns at time i into the ϵ- neighborhood of its location at time j (i.e. if $\vec{x}_i$ is closer to $\vec{x}_j$ than cut-off distance) $R_{i,j} = 1$ and these two vectors are considered to be recurrent. Otherwise $R_{i,j} = 0$. It is possible to visualize values of $R_{i,j}$ by black and white dots (Marwan, 2003; Zbilut and Weber, 1992), but often the recurrence plot relates distances $R_{i,j}$ to colors, e.g. the larger the distance, the "cooler" the color. Thus, the recurrence plot is a rectangular plot consisting of pixels whose colors correspond to the magnitude of data values in a two-dimensional array and whose coordinates correspond to the locations of the data values in the array. The black points indicate the recurrences of the investigated dynamical system, revealing its hidden regular and clustering properties. By definition RP is symmetric and has a black main diagonal (line of identity) formed by distances in the matrix compared with themselves. In order to understand RP it should be stressed that it visualizes a distance matrix which represents autocorrelation in the series at all possible time (distance) scales. As far as distances are computed for all possible pairs, elements near the diagonal on the RP plots correspond to short range correlation, whereas the long range correlations are revealed by the points distant from the diagonal. Hence if the analyzed dynamics (time series) is deterministic (ordered, regular), then the recurrence plot shows short line segments parallel to the main upward diagonal. At the same time if dynamics is purely random, the RP will not present any structure at all. One of the crucial points in RP analysis is selection of cutoff distance ε or radius. If ε is selected too low, no recurrent point will be found. At the same time it cannot be set too high because every point by mistake can be assumed as recurrent. Exhaustive overviews on this subject can be found in (Zbilut and Jr., 1998; Marwan, 2003) etc. The primordial aim of RP testing was the visual inspection of structures located in high dimensional phase spaces where other methods are useless, especially when we deal with real data sets. The view of recurrence plots provides a unique possibility to observe time evolution patterns of phase space trajectories both at large and small scales. By the large scale patterns or topology the recurrence plots can be characterized as homogeneous (dynamics with uniformly distributed characteristics), periodic (dynamics with distinct periodic components), drift (dynamics with slowly varying parameters) and/or disrupted-intermittent (dynamics characterized by abrupt changes)(Marwan, 2003). At small scales patterns (or texture) of recurrence plots can be characterized as single dots, diagonal lines, vertical lines and horizontal lines. The exact recurrent dynamics generate long diagonal lines separated by a fixed distance. A large amount of single isolated scattered dots and the vanishing amount of lines is typical for heavily fluctuating dynamics under influence of non-correlated noises (in this case insufficient dimension of the embedding space is not excluded). The non-regular occurrence at short as well as at long diagonal lines is characteristic for low dimensional chaotic processes, and the non-regular occurrence of extended uniform areas corresponds to irregular high dimensional dynamics. In a more general sense the line structures in an RP exhibit the local time relationship between the current phase space trajectory segments. Stationarity of the whole time series requires that the density of line segments be uniform. RP was developed for single data sets but Zbilut et al., (1998) have expanded it by considering two different time series. The cross-recurrence between two series $\{x_i\}$ and $\{y_i\}$ is defined as

$CR_{i,j} = \Theta\left(\varepsilon_i - \left\|\vec{x}_i - \vec{x}_j\right\|\right)$. Here, the two time series are embedded in the same phase space. The representation is analogous to the RP, and is called a cross-recurrence plot (CRP)(Marwan, 2003). Qualitative patterns of an unknown dynamics presented as a fine structure of RP or CRP often are too difficult to be considered in detail. Zbilut and Webber have developed a tool which quantifies the structures in RPs called Recurrence Quantitative Analysis (RQA)(Zbilut and Weber, 1992). They define measures using the recurrence point density, the length of diagonal and vertical structures in the recurrence plot, the recurrence rate, the entropy of recurrent points distribution etc. Presently at least 8 different statistical RQA characteristics are known (Zbilut and Weber, 1992; Ivanski and Bradley, 1998; Marwan, 2003), though their practical meaning is not always quite clear. Computation of these measures in small windows moving along the main diagonal of the RP reveal the time dependent behavior of these variables, making possible the identification of unknown dynamical patterns in time series (Zbilut and Weber, 1992; Marwan and Kurths, 2002). Here we briefly touch only on main RQA statistical values. The first of these statistics, termed recurrence ($\%REC$), is simply the percentage of points on the RP that are darkened or, in other words, those pairs of points whose spacing is below the ε_i - predefined cut-off distance. It quantifies the number of time instants characterized by a recurrence in the signals: the more periodic the signal dynamics, the higher the $\%REC$ value. The second RQA statistic is called *determinism* ($\%DET$); it measures the percentage of recurrent points in an RP that are contained in lines parallel to the main diagonal. The main diagonal itself is excluded from these calculations because points there are trivially recurrent. Intuitively, $\%DET$ measures how "organized" an RP is. This variable discriminates between the isolated recurrent points and those forming diagonals. Since a diagonal represents points close to each other, $\%DET$ also contains information about the duration of a stable interaction: the longer the interactions, the higher the $\%DET$ value. The third often used RQA statistic, called *entropy*, is closely related to $\%DET$.

Entropy (ENT) is the Shannon information entropy of a line distribution measured in bits and is calculated by binning the diagonal lines according to their lengths and using the formula: $ENT = -\sum_{k=1}^{N} P_k \log_2 P_k$ where N is the number of bins and P_k is the percentage of all lines that fall into bin k. In other words P_k is defined as the ratio of the number of k-point-long diagonals to the total number of diagonals. ENT is measured in bits of information, because of the base-2 logarithm. Thus, whereas $\%DET$ accounts for the number of diagonals, ENT quantifies the distribution of the diagonal line lengths. The larger the variation in the lengths of the diagonals, the more complex the deterministic structure of the RP. A more complex dynamic requires a larger number of bits (ENT) to be represented. The fourth RQA statistic, termed $TREND$, measures how quickly an RP goes away from the main diagonal. As the name suggests, $TREND$ is intended to detect nonstationarity in the data. The fifth RQA statistics is called *length of the maximal deterministic line* ($MAXLINE$) and is equal to the longest line length found in the computation of DET. Eckmann, Kamphorst, and Ruelle claim that line lengths on RPs are directly related to the inverse of the largest positive Lyapunov exponent (Zbilut and Weber, 1992; Marwan , 2003). Small $MAXLINE$ values are therefore indicative of random-like behavior. In a purely periodic signal, lines tend to be very long, so $MAXLINE$ is large. This completes our short overview of qualitative and quantitative methods of nonlinear time series analysis based on testing of phase space images.

3. Investigation of dynamics of complex natural processes and laboratory models

The last two decades witnessed development of robust nonlinear methods of time series analysis for detection and identification of complex dynamical processes. The importance of qualitative and quantitative analysis of such complicated processes is well recognized in almost every field of science. Below we describe some of our results demonstrating the ability of the universal methods of time series analysis briefly discussed above to detect hidden dynamical properties in seemingly random processes. In order to avoid repetition we state that, from the classical linear data analysis point of view, almost all processes and time series considered below appear random.

3.1. DETECTION OF NONRANDOM NONLINEAR STRUCTURE IN GEOPHYSICAL PROCESSES

Significant variability, both in time and space, makes the problem of identification and quantification of complex geophysical phenomena extremely difficult. There are no mathematical models formulated (and found appropriate) for describing space time dynamics of these phenomena; all attempts to formulate a “universal” mathematical model for describing geophysical phenomena have proven futile (Sivakumar and Jinno, 2002). Therefore it is accepted that the only way to understand dynamical features of complex geophysical processes is through the analysis of measured data sets using modern nonlinear methods.

3.1.1. *Dynamical structure of seismicity*

Earthquakes are one of the strongest natural calamities, causing a great human and material losses. The earthquake in China in 1976 took 255000 human lives, Armenia (1988) - 25000, Iran (1990) - 50000 etc. Earthquakes are the expression of the continuing evolution of the planet earth, more precisely of the deformation of its crust. According to modern plate tectonics, the Earth's lithosphere is mobile and is divided into several blocks (plates) that are forced to move due to convection in the underlying viscous asthenosphere. The relative motion of these plates results in accumulation of stresses on their boundaries. These stresses can be released by a fast slip (earthquakes) or by seismic creep. Most strain energy accumulated in the fault is transformed into heating, deformation and destruction of rocks. Only a small part (1 to 10%) is converted into seismic waves that propagate in the lithosphere. The energy radiated during a moderate earthquake is comparable with that of several large nuclear explosions. The lithosphere is an extremely complex system from the point of view of both its structure and processes therein (Turcotte, 1992; Korvin, 1992; Kagan, 1994; Keilis-Borok, 1994). Dynamics of seismic processes is viewed as extremely complicated, so that the level of "turbulence" of the lithosphere exceeds that of the atmosphere (Kagan, 1994; Kagan, 1997). During more than one hundred years of instrumental observations several important characteristics of spatial, temporal and energetic distributions of earthquakes have been revealed (C.H., 1990; Turcotte, 1992; Keilis-Borok, 1994; C., 1998; Matcharashvili and Javakhishvili, 2000; Rundle and Klein, 2000). Nevertheless the character of dynamics of seismic processes remains the subject of intense discussions because it is directly related to the problem of earthquake prediction. Critics of earthquake prediction (Kagan, 1994; Kagan, 1997; Geller, 1999; Kanamori and Brodsky, 2001), etc. regard seismic process as completely random, while its proponents consider it as complex and high-dimensional though not random (Main, 1997; Wyss, 1997; Chelidze and Matcharashvili, 2003; Knopoff, 1999), etc. Indeed, a completely random process is unpredictable on any spatial and temporal scales. On the other hand, for processes with nonrandom dynamical structure there always exist specific spatial and temporal scales at which systems behavior is deterministic, i.e. predictable. From this point of view a nonrandom seismic process can not be regarded as completely unpredictable. Of course it is clear that predictability in this sense does not necessarily mean a "real" forecast of every hazardous event for practically meaningful time scales. At present, the evidence of a nonrandom structure of seismicity has mainly scientific importance because it gives ground to looking for predictive markers. This is also important for testing modern ideas on possible control of practically unpredictable seismic processes. To bring some light in this field let us consider seismic processes from the point of view of their dynamic structure. As mentioned above one of the most popular approaches to the problem of identification of patterns of complex dynamics, including seismicity, is based on the evaluation of the nonlinear structure (or what is the same, nonlinear structure of the appropriate time series)(Rapp and Farwell, 1993; Theiler and Farmer, 1992). In this way it is possible to achieve reliable detection of dynamical regime(s) of seismic processes by calculation of their measurable characteristics. These characteristics can also be calculated prior to and after strong earthquakes. This is important in the search for possible earthquake predictive dynamical markers. In order to answer the above question on nonlinear structure in earthquake generation (or in other words its predictability) it is necessary to investigate dynamical properties of seismic processes in all three characteristic domains: energetic, spatial and temporal. For this purpose "time series" of inter-event time intervals (waiting time), magnitude sequences and inter-event distances of earthquakes in the entire Caucasian region have been used. All these time series were taken from the earthquake catalogue for the Caucasus and the adjacent territories for the 1962-1993 time period (Seismological Data Base of Institute of Geophysics, Tbilisi, Georgia). It was shown (see Fig. 1)that despite the fact that the size and temporal distribution of earthquakes both obey a power law, they are dynamically quite different. The magnitude distribution of earthquakes in the Caucasian region is undoubtedly high-dimensional, d_2 as a rule is larger than 8 ($d_2 > 5$ is the high dimensionality threshold)(Sprott and Rowlands, 1995). According to our results as well as to the reports of other authors (Korvin, 1992; Smirnov, 1995) the fractal dimension for the distribution of inter earthquake distances is low ($d_2 < 2$). Most interesting is that the waiting time interval distribution reveals an obviously low dimensional nonlinear structure (d_2 of the order of 1.6-2.5 and positive λ_{max} of the order of 0.2-0.7), although it can not be recognized as a deterministic chaos (Matcharashvili and Javakhishvili, 2000)(see Fig. 1). This low dimensionality of earthquakes' temporal distribution is in

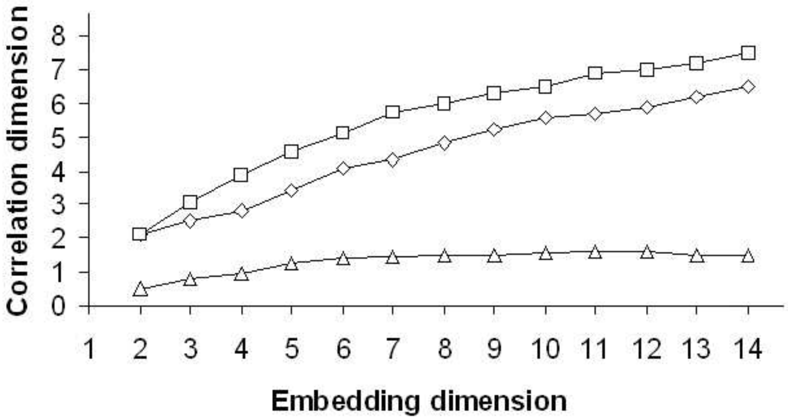


Figure 1. Typical plot of correlation dimension d_2 versus embedding dimension p for the Caucasus, the Greater Caucasus, and the Javakheti region, magnitude (middle curve) and inter-event time intervals (lower curve) sequences. The upper curve represents the random numbers set.

complete agreement with earlier results for other parts of world (C., 1998).

After the low dimensional temporal distribution iof earthquakes is found it is important to reveal the character of this dynamics before and after strong earthquakes. So as a next step on the way to a better understanding of the underlying dynamics of earthquake generation, we have undertaken comparison of the properties of waiting time distribution before and after large events. For this purpose we have considered waiting time sequences of a seismic catalogue separately before and after the largest events, using the above-mentioned tests such as correlation dimension and Lyapunov exponent calculation as measures of non-linearity. According to our results the general properties of dynamics of earthquakes' temporal distribution before and after the largest regional events does not indicate a qualitative difference from the integral dynamics obtained by consideration of time series from the complete original catalogues(see Fig. 2). Indeed, correlation dimensions of all considered waiting time sequences from the original catalogue (containing all independent events and aftershocks above the threshold magnitude), both preceding and following the largest events in the Caucasus, converge to a limit value. At the same time it is important that these values are not coinciding. Consequently, as long as all investigated time series have correlation dimension lower than the

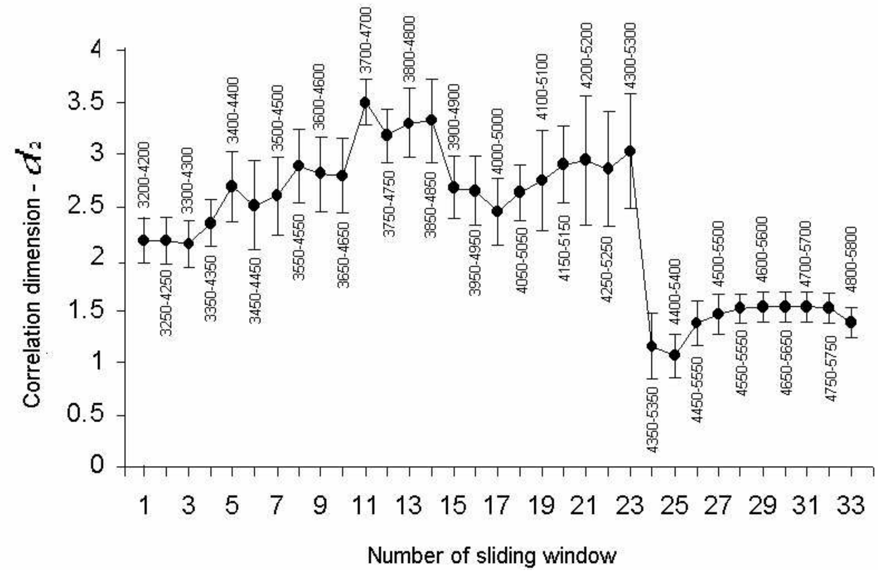


Figure 2. Variation of 1000 time interval width sliding windows correlation dimension - d_2 along Paravani earthquake region inter-event time interval sequences at 50 event steps.

low dimensional threshold ($d_2 < 5$) see also (C., 1998), it can be deduced that earthquakes' temporal distribution is characterized by a low dimensional dynamics before, as well as after the largest regional event. At the same time in the energetic domain earthquakes' magnitude distribution remains high dimensional before and after strong events. As stressed above, results of dimensional calculations, especially when a low-dimensional process is detected, should be verified using special methods. While testing low-dimensional waiting time sequences for deterministic chaos we have the typical problems always encountered in testing real, usually short and noisy time series. In order to overcome discrimination problems, as in the case of high-dimensional processes, one has to test time series for evidence of nonlinearity (Theiler and Prichard,). One additional reason why this approach has become popular is that, from the practical point of view, the goal of detecting nonlinearity in low dimensional data is easier than a confident identification of chaotic dynamics (Theiler and Farmer, 1992). It was found that, in all cases, time interval sequences obtained from the original catalogue above threshold magnitudes before and after the largest events reveal evidence of a nonlinear structure. In other words, the null hypothesis that these sequences are generated by linearly correlated noise or by static monotone nonlinearity should be rejected. The significance of differences of S-measure of natural sequences before and after the earthquakes considered from the appropriate phase randomized (S_{PR}) and Gaussian scaled random phases (S_{GSRP}) surrogates are significant at the $p < 0.005$ confidence level; thus the significance of differences for waiting time sequences before and after the Dagestan ($M = 6.6$) earthquake are $S_{PR} = 55.6 \pm 0.27$, $S_{GSRP} = 15.9 \pm 0.20$ and $S_{PR} = 50.5 \pm 0.15$, $S_{GSRP} = 17.1 \pm 0.13$; for the Paravani ($M = 5.6$) earthquake $S_{RP} = 51.1 \pm 0.21$, $S_{GSRP} = 16.2 \pm 0.13$ and $S_{PR} = 64.2 \pm 0.27$, $S_{GSRP} = 11.5 \pm 0.17$; for the Spitak ($M = 6.9$) earthquake $S_{PR} = 49.2 \pm 0.12$, $S_{GSRP} = 11.4 \pm 0.12$ and $S_{PR} = 52.2 \pm 0.27$, $S_{SRP} = 15.2 \pm 0.19$; for the Racha ($M = 6.9$) earthquake $S_{PR} = 57.6 \pm 0.23$, $S_{GSRP} = 16.3 \pm 0.23$ and $S_{PR} = 51.5 \pm 0.17$, $S_{GSRP} = 18.4 \pm 0.11$. To understand the above differences in the correlation dimension values before and after the largest earthquakes, we used a sliding window technique. We considered the sequence of 6695 events of the Paravani earthquake's inter-event time intervals. Here $No = 5300$ is the ordinal number of the time interval, which directly preceded the largest earthquake. We have calculated d_2 for 1000 event sliding windows with a step of 50 events starting with event $No = 3200$ up to event $No = 5800$. Hence the first window consists of time interval sequences between earthquakes in the range $3200 - 4200$. As shown in Fig.2, values of d_2 decrease for the windows following the largest event. The decrease begins when a sliding window contains about 20 inter-event time intervals after the largest event and becomes significant when 40-50 such events are included in the sequence. Note that the window $4310 - 5310$, like the window $4300 - 5300$, reveals the background value of a correlation dimension for waiting time sequences before the largest earthquake. It seems doubtful that such an essential change in the dynamical properties of the considered sequence can be caused by the addition of so few new data, unless there is a hidden regularity in a sufficiently long waiting time sequence containing data preceding the largest event. These results indicate that measuring of complexity of seismic time series may provide markers having precursory meaning and in the future may help to elaborate earthquake prediction tests (Matcharashvili and Ghlonti, 2002).

Thus it is clear that seismicity in two domains (temporal and spatial) out of three (energetic, temporal and spatial) reveals low dimensional nonlinear structure. This and similar results obtained in the last decade lead to understanding that, in spite of extreme complexity, the processes related to the earthquake generation are characterized by some internal dynamical structure and thus are not completely random (Smirnov, 1995; C., 1998; Rundle and Klein, 2000; Matcharashvili and Ghlonti, 2002). Despite the proofs that seismic activity is a non-random process, the physics of the internal or external factors involved is still poorly understood; but it can be asserted that the general problem of earthquake prediction and/or earthquake triggering, one of the most challenging targets of current science, should not be considered as an "alchemy of present time" (Geller, 1999). In other words, the quest for earthquake predictive markers or triggering factors should be recognized as an obviously difficult, but scientifically well-grounded task related to the search for determinism in the complex seismic process.

3.1.2. *Detection of changes in earthquake dynamics caused by external anthropogenic influences*

As discussed above, dynamics of earthquake related processes in the earth's crust are nonrandom, having low and/or high dimensional structures. One sign of such processes, in nonrandom systems which are close to the critical state, is their high sensitivity to initial conditions as well as to relatively weak external influences. This general property of complex systems acquires special significance for practically unpredictable seismic processes. Indeed, insofar as we cannot govern initial conditions of lithospheric processes, even the possibility of control of seismic processes has immense scientific and practical importance (e.g. to induce by specific external influences the release of accumulated seismic energy via a series of small or moderate earthquakes instead of one strong devastating event). To begin to understand such possible control we investigate the dynamics of seismic processes and modeling natural seismicity in laboratory systems. According to recent investigations, Earth's crust in seismically active regions can be in the critical state or close to it (Bak and Wiesenfeld, 1988; C.H., 1990). This can explain the known phenomena of effectiveness of relatively small influences (such as tidal variations, filling large reservoirs, pumping of water into boreholes etc. (Sibson, 1994), adding an insignificant contribution to the existing tectonic strains, on seismic process. In the experiments, initially aimed towards finding resisitivity precursors of strong earthquakes in the upper layers of earth's crust by MHD-sounding, an unexpected effect of microseismicity activation after these discharges has been discovered in the Bishkek, Central Asia test area (Tarasov, 1997). Experiments demonstrating the triggering effect of MHD (magnetohydrodynamic) soundings on the microseismic activity of the region have been performed in 1975 -1996 by IVTAN (Institute of High Temperatures of the

Russian Academy of Sciences) in the Central Asia test area (Tarasov, 1997; Jones, 2001). During these experiments deep electrical sounding of the crust was carried out at the Bishkek test site from 1983 to 1989. The source of electrical energy was an MHD generator, and the load was an electrical dipole of 0.4 Ohm resistance with electrodes located at a distance of 4.5 km from each other. When the generator was fired, the load current was 0.28 - 2.8 kA, the sounding pulses had durations of 1.7 to 12.1 s, and the energy generated was mostly in the range of 1.2 - 23.1 MJ (Volykhin and Zubovich, 1993). In order to test the possibility of external anthrophic impact on seismic regime the dynamics of temporal distribution of earthquakes around the test area was analyzed. For this purpose sequences of time intervals in seconds between consecutive earthquakes, compiled from the seismic catalogue of the Institute of Physics of Earth (Moscow), were investigated using tools of nonlinear time series analysis (Chelidze and Matcharashvili, 2003). The main goal was to find out whether strong EM discharges may lead to changes in dynamics of temporal distribution of seismicity. The time period before beginning the experiment (1975-1983), the time period of cold and hot runs (1983-1988) and the time period immediately after accomplishment of experiments (1988-1992), as well as the time period long after the experiment (1992-1996) were considered separately. Interevent time sequences, corresponding to these periods, have approximately equal lengths (about 3660 events). The integral time series (5297 time intervals) for the whole period of observation (1975-1996) containing waiting time sequences between all events above the threshold reveals clear low correlation dimension ($d_2 = 1.22 \pm 0.43$) (Fig. 3). Shorter time series also were considered. Namely 1760 waiting times before (1975-1983), 1953 waiting times during MHD experiments (1983-1988) and 1584 waiting times of the period after experiments (1988-1992). Time series before and especially during MHD experiments also have low correlation dimension ($d_2 < 5$). Namely $d_2 = 3.83 \pm 0.80$ before and $d_2 = 1.04 \pm 0.35$ during experiments. On the other hand, opposite to what was mentioned above, after cessation of experiments (Fig. 3, triangles) the correlation dimension of waiting times sequences noticeably increases ($d_2 > 5.0$), exceeding the low dimensional threshold ($d_2 = 5.0$). That means that after termination of experiments the extent of regularity or extent of determinism in the process of earthquake temporal distribution decreases. The process becomes much more random both qualitatively (Fig. 4) and quantitatively (Fig. 3. triangles). For comparison, in Fig. 3, results for random number sequence are shown too (diamonds). The found low correlation dimension of integral

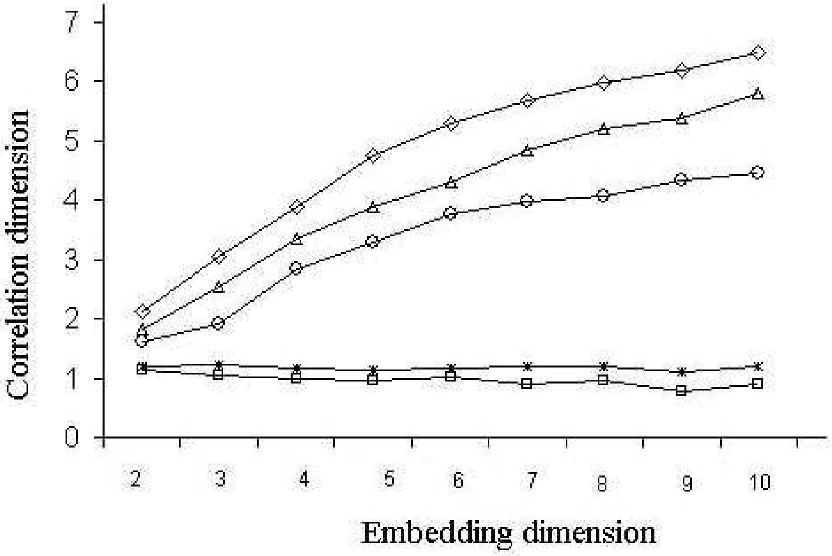


Figure 3. Correlation dimension versus embedding dimension of waiting times sequences: asterisks - integral time series (1975-1996), circles-before beginning of experiment (1975-1983), squares - during experiments (1983-1988), triangles - after experiments (1988-1992), diamonds correspond to random number sequence.

waiting time series in central Asia is in good agreement with the above results on low dimensional dynamical structure of earthquake temporal distribution for other seismoactive regions (C., 1998; Matcharashvili and Javakhishvili, 2000). On the other hand Fig. 3 shows that a relatively short ordered sequence can decrease correlation dimension of a long integral time series, which contains much larger sequences of high dimension. Thus the low value of d_2 of a long time series does not mean that the whole sequence is ordered - ordering can be intermittent. The data on correlation dimension, together with qualitative RP results shown in Fig. 4, provide evidence that after the beginning of EM discharges the dynamics of temporal distribution of earthquakes around IVTAN test area undergoes essential changes; it becomes more regular, or events of corresponding time series become functionally much more interdependent.

These results were tested against the possible influence of noise using a noise reduction procedure (Schreiber, 1993; Kantz and Schreiber, 1997) as well as against trends or non-stationarity in interevent data sets (C., 1998). The tests confirm our conclusions. Thus the changes before, during and after experiments (Fig. 3) are indeed related to dy-

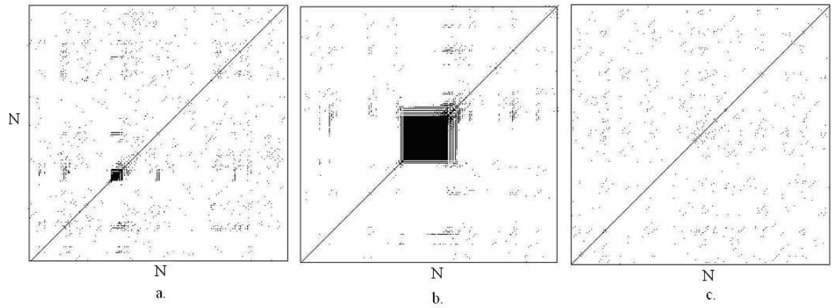


Figure 4. Qualitative RP analysis of temporal distribution of earthquakes (M > 1.7) before the beginning of EM experiments (1975-1983), during experiments (1983-1988) and after experiments (1988-1992). Recurrence plots analysis of waiting times sequences: a) before experiments, b) during experiments, c) after experiments.

namics of the temporal distribution of earthquakes caused by external anthropic influence (MHD discharges)(Chelidze and Matcharashvili, 2003).

Subsequently, in order to have a basis for a more reasonable rejection of spurious conclusions caused by possible linear correlations in the data sets considered, we have used the surrogate data approach to test the null hypothesis that our time series are generated by a linear stochastic process (Theiler and Farmer, 1992; Rapp and Farwell, 1993; Rapp and Jumenez-Montero, 1994; Kantz and Schreiber, 1997). Precisely, PR and GSRP surrogates sets for the waiting times series were used (Chelidze and Matcharashvili, 2003). Surrogate testing of waiting time sequences before (a) and during (b)experiments using d_2 as a discriminating metric for each of our data sequences has been carried out. 75 of PR and $GSRP$ surrogates have been generated. The significance criterion S for analyzed time series before experiments is:22.4 ± 0.2 for PR and 5.1 ± 0.7 for $GSRP$ surrogates. After beginning of experiments the null hypothesis that the original time series is linearly correlated noise was rejected with significance criterion S: 39.7 ± 0.8 for PR and 6.0 ± 0.5 for $GSRP$ surrogates. These results can be considered as strong enough evidence that the analyzed time series are not linear stochastic noise. The above conclusion about the increase of regularity in an earthquake's temporal distribution after beginning of experiments (external influence on seismic process) is confirmed also by results of RQA; namely $RR(t) = 9.6$, $DET(t) = 3.9$ before experiments, $RR(t) = 25$, $DET(t) = 18$ during and $RR(t) = 3$, $DET = 1.5$ after experiments. It was shown in our previous research that small earthquakes play a very important role in the general dynamics of

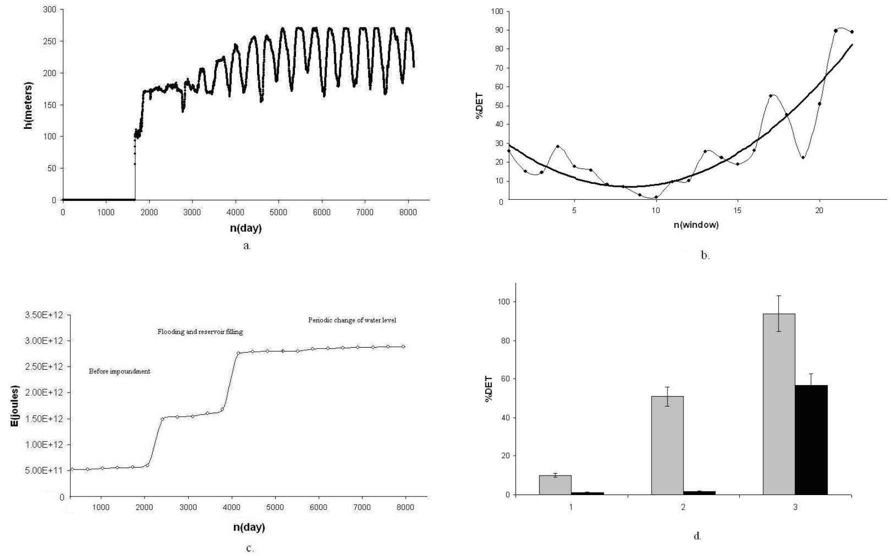


Figure 5. a) Variation of water level in Enguri high dam reservoir above sea level in 1978-1995. b) RQA $\%DET$ of daily number of earthquakes calculated for consecutive one year sliding windows, c) Cumulative sum of released daily seismic energy. d) RQA $\%DET$ of magnitude (black columns) and interearthquake time interval (grey columns) sequences (1) before impoundment, (2) during flooding and reservoir filling and (3) periodic change of water level in reservoir.

earthquake temporal distribution (Matcharashvili and Javakhishvili, 2000). This is why we also have carried out the analysis of time series containing all data available from the entire catalogue of waiting time sequences, including small earthquakes that are below the magnitude threshold. This test is also valid for checking the robustness of results in the case of adding a new, not necessarily complete, set of data to our original set. The total number of events in the whole catalogue increased to 14100, while in the complete catalogue for all three above-mentioned periods (before, during and after MHD experiments) there were about 4000 data in each one. Both the complete and whole catalogues of waiting time sequences reveal low dimensional nonlinear structure in the temporal distribution of earthquakes before and especially during experiments.

This means that our results on the influence of hot and cold EM runs on the general characteristics of earthquakes' temporal distribution dynamics remain valid for small earthquakes too. Thus the conclusion drawn from this analysis is that the anthropogenic external influence, in the form of strong electromagnetic pulses, invokes distinct changes in the dynamics of earthquakes' temporal distribution - dynamical characteristics of regional seismic processes are changed. Though energy released during these experiments was very small compared to the energy in even small earthquakes, it still can be considered as a strong enough man made impact. It was recently found that it is possible to control the dynamics of complex systems through small external periodic influences. In this respect we have investigated the possible influence of water level periodic variation on dynamics of regional seismic activity. For this purpose data sets of the water level variation in the Western Georgia Enguri high dam reservoir and the seismicity data sets for the surrounding area for 1973-1995 were investigated. The height of the dam is 272 m, the (average) volume of water in the reservoir $1.1 \times 109m^3$. The Enguri reservoir was built in 1971-1983. Preliminary flooding of the territory started at the end of December 1977; since 15 April 1978 the reservoir was filled step by step to a 510 m mark (above the sea level). Since 1987 the water level in the reservoir has been changing seasonally, almost periodically. Thus we have defined three distinct periods for our analysis, namely, (i) before impoundment, (ii) flooding and reservoir filling and (iii) periodic change of water level. Fig. 5a shows the daily record of the water level in the Enguri dam reservoir for the period 1978-1995. The relevant size of the region to be investigated, i.e. the area around the Enguri high dam which can be considered sensitive to the reservoir influence (90 km), was evaluated based on the energy release acceleration analysis approach (Bowman et al., 1998) as it is described in (Peinke, et al., 2006). The number of earthquakes which occurred above the representative threshold (1200) was too small to carry out a correct correlation dimension and Lyapunov exponent calculation for these three periods. So the RQA calculation was carried out. It was shown that when the external influence on the earth's crust caused by reservoir water becomes periodic the extent of regularity of the daily distribution of earthquakes essentially increases (see Fig. 5a and b). It is also clear that during flooding and nonregular reservoir filling the amount of released seismic energy increases (Fig. 5a and c) in complete accordance with well-known concepts of reservoir-induced seismicity (Talwani, 1997; Simpson and C., 1988). It is important to mention that the influence of an increasing amount of water and its subsequent periodic variation essentially affects the character of earthquake's magnitude and temporal distribution (see Fig. 5d). In particular the extent of order in earthquake's magnitude distribution substantially increases when an external influence becomes periodic (black columns). At the same time dynamics of earthquake's temporal distribution changed even under irregular influence, though not so much as under periodic influence. Similar conclusions are drawn from other RQA measures. All these results indicate that a slow periodic influence (loading - unloading) may change dynamical properties of local seismicity. Assuming the possibility of control of dynamics of seismic processes under small periodic influences of the water level variation, the following question might arise: if there exists the control caused by periodic reservoir loading, why do the earthquakes correlate weakly with the solid earth tides (see Vidale et al., 1998; Beeler and Lockner, 2003). A possible explanation is that the control strength depends not only on the amplitude of forcing, but also on its frequency. If both parameters are varied, the synchronization area between external periodic influence and seismic activity forms the so-called Arnold's tongue with some preferred frequency that needs minimal forcing (Pikovsky and J., 2003; Chelidze and Devidze, 2005). At larger or smaller frequencies the forcing needed for achieving synchronization increases drastically and at large deviations from the optimal frequency the synchronization becomes impossible. According to (Beeler, 1988) the daily tidal stress is changing too fast in comparison with the characteristic time of the moderate seismic event nucleation, which is of the order of months or years. On the other hand, the frequency of periodic loading exerted by the reservoir exploitation is one year and that is close to the characteristic time of significant earthquake preparation. Therefore, the synchronization effect of reservoir periodic loading of seismic events can be accepted as a realistic physical mechanism for related dynamical changes.

3.2. DETECTION OF DYNAMICAL CHANGES IN LABORATORY STICK-SLIP ACOUSTIC EMISSION UNDER PERIODIC FORCING

The above results provide serious arguments that, under external periodic influence, the dynamics of natural seismicity can be changed. This is very important from both the scientific and engineering points of view. At the same time, real field seismic data often are too short and incomplete to draw unambiguous conclusions on related complex dynamics. Therefore, in order to test our field data results, similar analysis on the acoustic emission data sets, during stick-slip, has been carried out (Chelidze and Matcharashvili, 2003; Chelidze and Devidze, 2005). Acoustic mission accompanying stick-slip experiments is considered as a model of a natural seismic process (A. and Sornette, 1999; Rundle and Klein, 2000). Our laboratory setup consisted of two samples of roughly finished basalt. One of the samples (plates),the lower one, was fixed;

the upper one was pulled with constant speed by the special mover, connected to the sample by the rope-spring system; acoustic and EM emissions accompanying the slip were registered. The following cases were studied: i) pulling the sample without any additional impact; ii) the slip with applied additional weak mechanical (periodic) impact; iii) slip with applied periodic EM field. Thus, experiments have been carried out under or without periodic mechanical or electromagnetic (EM) forcing, which simulates the external periodic influence. If the large pulling force can be modulated by a weak periodic force of EM or mechanical nature, this could show high sensitivity of critical or "nearly critical" systems to small external impact. As was mentioned the aim was to prove experimentally the possibility of controlling the slip dynamical regime by a weak mechanical or EM impact. The elementary theoretical model of EM coupling with friction can be formulated in the following way. It is well known that application of an EM field to a dielectric invokes some forces acting upon molecules of the body; the resultant of them is called the ponderomotive or electrostriction force Fp that is affecting the whole sample. The force is proportional to the gradient of the field intensity squared and it carries away the sample in the direction of the largest intensity. Quite different regimes of time distribution of maximal amplitudes of acoustic emission were observed depending on the intensity of the applied external weak (relative to the pulling force) perturbations. As shown in Fig. 6, increased periodic forcing first leads to a more regular temporal distribution, while further increase decreases the extent of regularity. This experiment confirms the above field results on the possible controlling effect of external periodic influence on the seismic process.

3.2.1. *Changes in dynamics of water level variation during increased regional seismic activity*

As the next example of using the phase space structures testing methods of dynamical changes detection in earthquake related natural processes, we present results of our investigation of water level variation in deep boreholes. Variation of water level in deep boreholes is caused by a number of endogenous and exogenous factors.

The most important factor is the strain change in the upper Earth crust. Deep boreholes represent some kind of sensitive volumetric strainmeters, where the water level is reacting to the small ambient deformation. Hence, water level variations obviously will also reflect the inherent response of the aquifer to the earthquake related strain redistribution in the earth's crust (Kumpel, 1994; Gavrilenko and Kum-

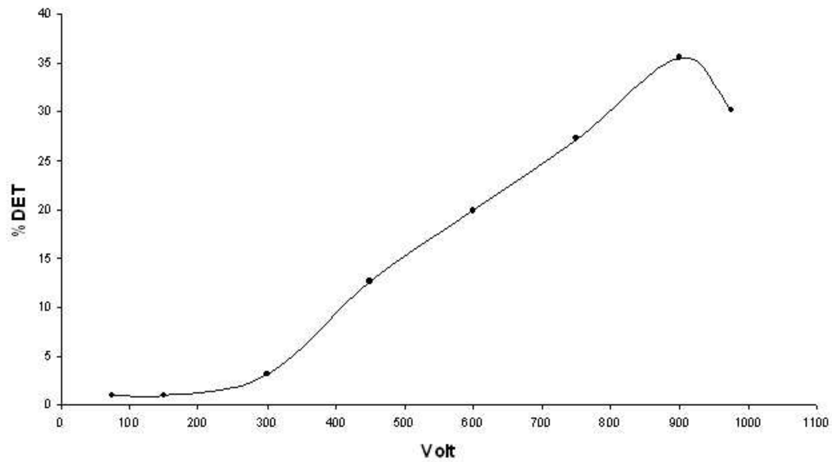


Figure 6. Dynamical changes in temporal distribution of acoustic emission under increasing external periodic forcing.

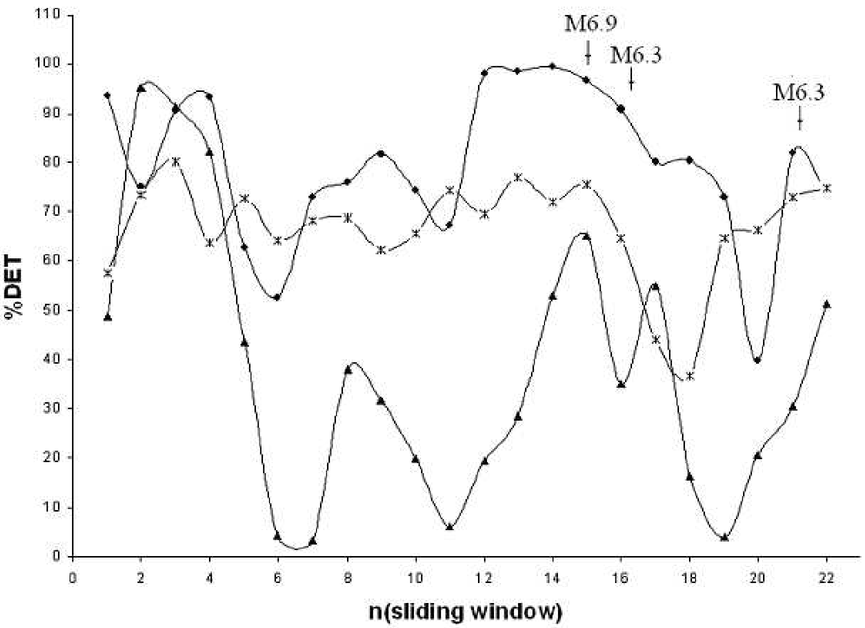


Figure 7. Variation of monthly extent of regularity in water level data sets, observed in deep boreholes calculated for 720 windows at 720 data steps. Triangles - Akhalkalaqi borehole, Circles - Lisi borehole, and asterisks - Kobuleti borehole.

siashvili, 2000). Therefore investigation of water level variations in deep boreholes may provide additional understanding of dynamics of processes related to earthquake preparation in the earth's crust (King et al., 1999). We have investigated dynamics of water level variation in deep boreholes in Georgia. Analysis was carried out on water level hourly time series from 3 (about 2000m depth) boreholes: Lisi (44.45 N, 21.45 E), Akhalkalaki (43.34 N, 41.22 E), and Kobuleti (41.48 N, 41.47 E) (01.03.1990-29.02.1992). Several strong seismic events took place during this time period in the Caucasus. Namely, $M = 6.9$ (29.04.1991) $M = 6.3$ (15.06.1991) and $M = 6.3$ (23.10.1992) earthquakes. The aim was to answer the question whether strain redistribution in the earth's crust related to earthquake preparation may lead to dynamical changes of water level variation in deep boreholes.As it is shown in Fig. 7 in most cases regularity of variation of water level in deep boreholes essentially decrease several months prior to a strong earthquakes. At the same time the extent of such decrease is different for different boreholes and obviously depends on the geological structure of area.

3.3. DETECTION OF DYNAMICAL CHANGES IN EXCHANGE RATE DATA SETS

Evidence of increased interest of economists in the field of investigation of complex processes has often been demonstrated during the last decade (Bunde and J., 2002). In fact, though economists have postulated the existence of economic cycles, still there are serious problems in the practical detection and identification of different types of behavior of economic systems (M., 1993; McCauley, 2004). Here we show results of our analysis of time series of the Georgian Lari - US Dollar exchange rate.

Data sets were provided by the National Bank of Georgia for the 03.01.2000 - 31.12.2003 time period. This 7230 data length time series consists of GEL/USD exchange rate values calculated 5 times per day. It follows from our analysis that the dynamics of the GEL/USD exchange rate is characterized by a clear internal structure. Indeed, as seen in Fig. 8a, the recurrence plot of GEL/USD exchange rate time series reveals visible structure in the phase point distribution. The same time series after dynamical structure distortion (data shuffling), PR and GSRP procedures do not reveal visible structure (see e.g. Fig 8b). We conclude that the revealed dynamical nonrandom structure of the analyzed GEL/USD exchange rate time series is an inherent characteristic and is not caused by linear effects. Quantitatively, GEL/USD exchange rate time series were analyzed using shifted, 7 days span,

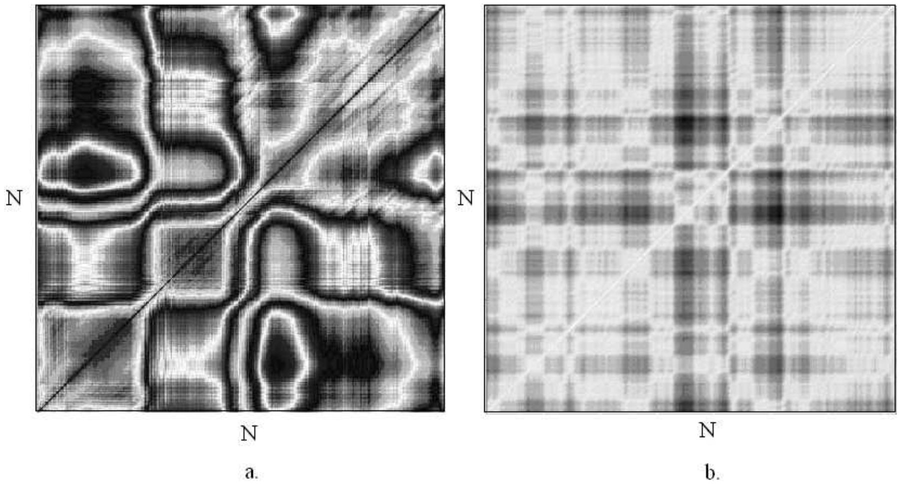


Figure 8. Recurrence plots of a) original and b) GSRP, GEL/USD exchange rate time series.

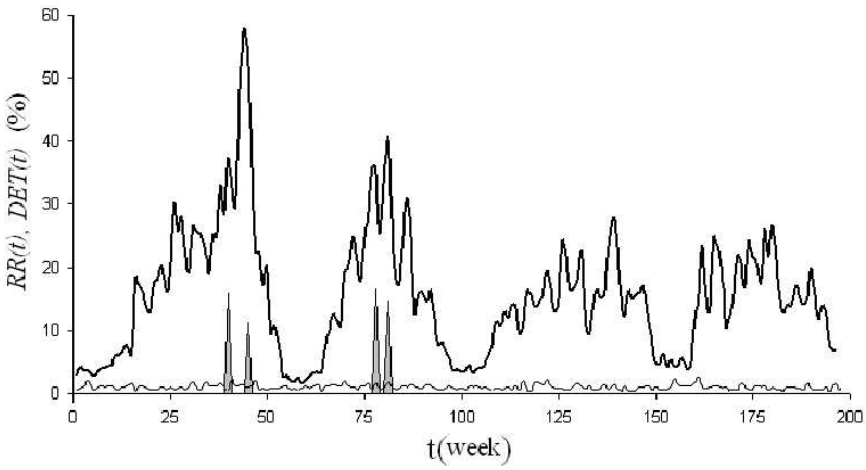


Figure 9. RQA metrics of Georgian Lari/US Dollar exchange rate time series. Percentage of recurrence points in 7 days span sliding windows of original (solid line) and phase randomised time series (thin line). Grey peaks corresponds to percentage of determinism in original time series.

sliding windows. Quantitative analysis of the recurrence plot structure shows that the dynamics of GEL/USD exchange rates is a complex process with a variable share of deterministic components (Fig. 9). The approximate period of this variation is one year (see Fig. 9). The maximal extent of GEL/USD exchange rate regularity was detected in the beginning of 2001.

3.4. DETECTION OF DYNAMICAL CHANGES IN ARTERIAL PRESSURE DATA SETS

Detection and identification of dynamical aspects of physiological processes remain two of the main challenges of current clinical and experimental medicine. In this regard significant attention was paid to changes in heart dynamics under different cardiac conditions (Elbert, 1994; Pikkujamsa and Huikuri, 1999; Weiss and Chen, 1999; Bunde and J., 2002). Physiological time series of different origin have been investigated. For previous years, based on the correlation integral approach, it was suggested that there is some evidence of nonlinear structure in normal heart dynamics (Lefebvre and Fallen, 1993; Govindan and Gopinathan, 1998). Moreover it has been established for physiological data sets of different origin that a high degree of variability is often a feature of young healthy hearts, and that an increase in variability of physiological characteristics is common for aging and diseases (Zokhowski.M. and Nowak, 1997; Pikkujamsa and Huikuri, 1999). According to the demands of the GPA algorithm, these results were obtained for long data time series, e.g. 24-h Holter monitor recordings. At the same time, despite a number of important findings, from the practical point of view the method of nonlinear analysis of medical time series discussed above is problematic. This is conditioned by problems related to the absence of stability in the obtained data sequences, i.e., the measured signal depends on the patients' emotional and physical condition at a given moment (Zokhowski.M. and Nowak, 1997; Zhang and Thakor, 1999). Due to the difficulty of obtaining long time series the RQA method became increasingly popular among physiological researchers. In the present study time series of indexes of the myocardial contractile function have been investigated, including time series of maximal velocity of myocardial fibers circular contraction, time of intraventricular pressure increase, mean velocity of myocardial fibers circular contraction and maximal rate of intraventricular pressure. These time series consist of apex cardiograph records (Mason, 1970; Antani and Kuzman, 1979). A total 120 adult males were studied, including: 30 healthy subjects, 30 patients with first, 30 with second, and 30 with severe third stage of arterial hypertension (according to the classification of 1996). These time series correspond to a composite set of concatenated subsequences containing 15-20 observables (calculated contractile indexes) for each of 30 people relevant to the same group. These subsequences form a total of 500 data length time series for separate indexes.

A similar approach of multivariable reconstruction was successfully

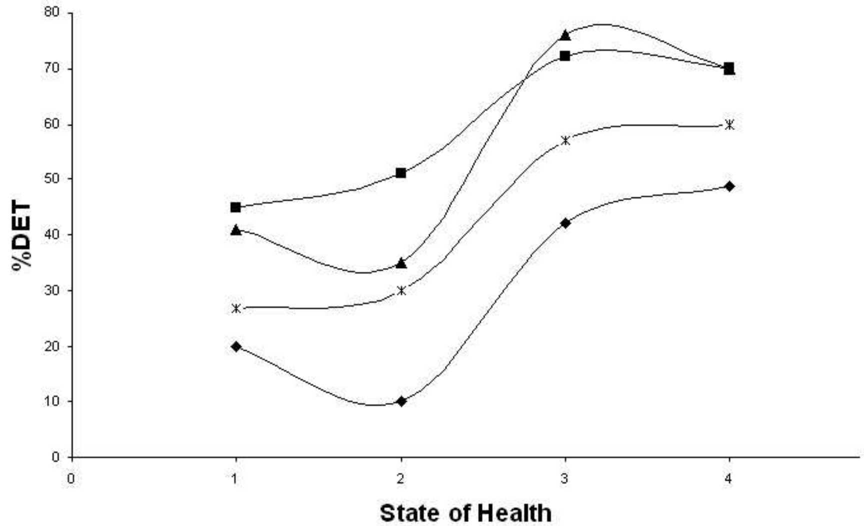
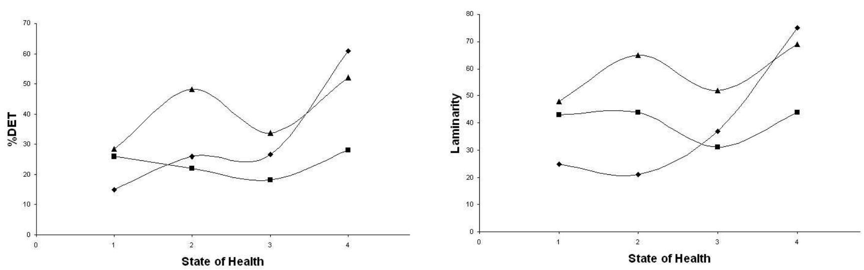


Figure 10. RQA $\%DET$ of indexes of myocardial contractile function time series versus the state of health. Diamonds - maximal velocity of myocardial fibers circular contraction, squares - time of intraventricular pressure increase, triangles - mean velocity of myocardial fibers circular contraction. Asteriscs - maximal rate of intraventricular pressure.



a. b.

Figure 11. a) RQA $\%DET$ and b) Laminarity of blood pressure time series versus the state of health. Diamonds - systolic pressure, squares - diastolic pressure, triangles - heart rate.

applied earlier for the calculation of correlation dimension of different composite time series (Elbert, 1994; Rombouts and Stam, 1995; Yang and Madronich, 1994). Besides systolic and diastolic pressure, the heart rate variability in healthy subjects and patients with different stages of arterial hypertension were investigated. The analyzed time series consist of 24h ambulatory monitoring of blood pressure recordings from 160 patients. Their age was between 30 and 70. The patients under study were not given medicines for 2-3 days preceding the examination. Blood pressure recording was carried out in a calm environment, in the sitting position according to the standard method provided by hypertension guidelines. The 24 hr monitoring of blood pressure was carried out from 11:00 a.m. to 11.00 a.m. of the next day, taking into consideration the physiological regime of the patients. Intervals between the measurements was 15 min. Systole, diastole, average tension as well as heart rate were defined. The analyzed multivariable time series were compiled as consecutive sequences of appropriate data sets of each patient from the considered groups. Integral time series contain about 1300 data for each healthy and pathological group analyzed. As seen in Fig. 10, the extent of regularity of time series of myocardial indeces increases in pathology. A similar result was obtained for systolic pressure time series (Fig. 11 diamonds). An increase of regularity is also visible for heart rate time series, although this is not so essential. At the same time the dynamics of diastolic pressure was practically unchanged. It is important to mention that time series used were multivariable as they contain data from different patients of the same physiologic group. Moreover myocardial indeces and arterial pressure data sets were taken from different groups. Taking into account all these facts it is very important that dynamical changes with the extent of pathology increase are similar. In other words, in almost all cases considered dynamics of physiological processes in pathology became more regular than in healthy conditions.

These results are in accord with our and other authors' results (Elbert, 1994; Garfinkel and Weiss, 1997; Pikkujamsa and Huikuri, 1999; Weiss and Chen, 1999; Matcharashvili, 2001) and show that nonlinear time series analysis methods enable the detection of dynamical changes in complex physiological processes.

4. Conclusions

Modern methods of qualitative and quantitative analysis of the complexity of natural processes are able to detect tiny dynamical changes imperceptible with classical data analysis methods. In this chapter the main principles of modern time series analysis methods, based on reconstructed phase space structure testing, have been briefly described. It was shown, using data sets of different origins, that correctly using these methods may indeed provide a unique opportunity for qualitative detection and quantitative identification of dynamical peculiarities of complex natural processes.

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