Nonlinear Analysis: Modelling and Control, Vilnius, IMI, 1998, No 2

CORRELATION IN THE HEART RATE DATA

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Abstract

Variety of methods of nonlinear dynamics have been used for possibility of an analysis of time series in experimental physiology. Dynamical nature of experimental data was checked using specific methods. Statistical properties of the heart rate have been investigated. Correlation between of cardiovascular function and statistical properties of both, heart rate and stroke volume, have been analyzed. Possibility to use a data from correlations in heart rate for monitoring of cardiovascular function was discussed.

INTRODUCTION

Application of the chaos theory for quantitative characterization of systems with complicated behavior has aroused considerable interest of physiologists in nonlinear dynamics methods. Clinicians' interest in nonlinear dynamic was caused by recent investigations which reveal chaotic components in heart rate data previously described as periodic ones, sinus rhythm. Power spectrum of the electrocardiogram data shows a broad band structure typical for stochastic and chaotic processes [1, 2]. Therefore theory of the deterministic chaos looks very attractive searching for the new characteristics to describe cardiac abnormalities. However, specific features of the biological signals such as high internal noise and short stationary times cause serious difficulties. Standard algorithms require special modifications for biological data to comply with the requirements of physiologists for high sensitivity to the abnormalities in system functioning and reliability of the obtained results. Therefore in practical physiology chaotic parameters serve mainly as system complexity indicators, but not as a quantitative parameters. On the other hand, typical chaotic parameters such as dimensions or Lyapunov exponents are averages over long period of time and can only serve as a quantitative characteristic of the general state of biological system. Analysis of local in time structures is essential for the diagnostic procedures. Therefore methods sensitive to the local dynamical structure of the system should be used for analysis of heart rate, changing with development of cardiac pathology, in addition to the sophisticated chaotic parameters. In this study

we tried to overview results of our recent years investigation in which we tried to compare diagnostic features of different nonlinear dynamics and statistical methods used for practical physiology.

EKSPERIMENTAL DATA AND REQUIREMENTS FOR ANALYSIS

We have registered simultaneously two parameters of heart activity, namely inter-beat intervals (RR) and stroke volume (SV) quantities per heart beat. Simultaneous recording allows to obtain more comprehensive picture of heart functioning, because RR intervals are reflecting the level of autonomic control, while SV data gives an additional information about cardiac contractility function. Data were obtained from four different patient groups, two groups of normal adult subjects (well trained sportsmen and healthy subjects with normal autonomic control), and two groups of coronary artery disease (CAD) patients (CAD pts and CAD pts after myocardial infarction).

Specifics of the biological systems require modifications of standard nonlinear dynamics algorithms. The main problems of the nonlinear analysis when applying it to biological signals can be summarized as follows: a) high level of random noise in the biological data. The applied nonlinear dynamics methods should be robust to the noise influence; b) short experimental data sets due to the low frequencies of the biological signals. Short realizations cause large error bars in the estimation of the chaos parameters; c) nonstationarity of the biological systems. Cardiac activity is influenced by a various external factors with different characteristic times; d) spatially extended character of the system.

NONLINEAR DYNAMICS OR RANDOM NOISE?

For the noisy and short time series, standard of algorithms chaotic dynamics can give spurious results, i. e. they can indicate the presence of the nonlinear dynamics in completely random systems. Recently, the surrogate data techniques have been developed to distinguish the chaotic systems from the linearly correlated noise [3]. In this technique as the first step an ensemble of the so called "surrogate" data sets is created from the original data. The "surrogate" data are completely stochastic, but they contain exactly the same linear correlations as that in the original time series. The practical way to do this is to take the Fourier transform of the original data, randomize the phases while keeping the magnitudes intact, and then invert the Fourier transform. The resulting time series have the same power spectrum as the initial data set was, but they are random in all other respects. Then one can compute any chaos parameter, for example, correlation dimension, using the same algorithm for both original and surrogate data sets. If the difference between the real and the surrogate dimension is significantly larger than the standard deviation of the surrogate dimensions calculated from different sets, then it is a strong indication of the nonlinear structure in the investigated time series.

Described surrogate data technique [3] have been used to check our data (Fig. 1a) for nonlinearity. An ensemble of so called "surrogate" data sets (Fig. 1b) having the same power spectrum but random in all other respects have been created. Correlation dimension was calculated for both original and surrogate data using the same algorithm, namely Grassberger-Proccacia algorithm suggested in [4]. The dependence of the correlation exponent n on embedding dimension M is shown in Fig. 1c for original signal and mean value of ten surrogate signals. The mean deviation of the surrogate data is 5%. Dependence $\nu(M)$ for the original data is closer to the saturating behavior typical for chaotic data, while surrogate signals ensemble demonstrate more stochastic behavior. We suppose that this result is sufficient for nonlinear structure evidence in HR data.

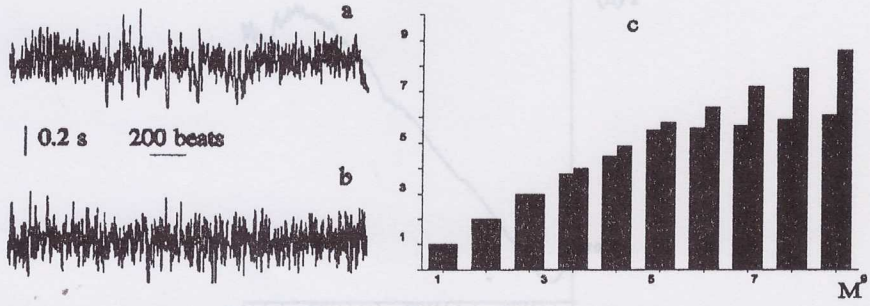

Fig. 1. a) HR data for healthy adult subjects, b) "Surrogate" data obtained from the HR data, c) $\nu(M)$ for real (light column) and "surrogate" (dark column) data.

RESULTS

Correlation dimension and exponent of the long-range correlations have been chosen and checked as quantitative system characteristics. For the first step correlation dimension was calculated using suggested [4] Grassberger-Proccacia algorithm:

$$C^M(\varepsilon) = N^{-1/2} \sum_{i \neq j} \Theta\left(\varepsilon - \left\| x_i^M - x_j^M \right\|\right) \sim \varepsilon^{\nu(M)}. \qquad (1)$$

Here $\left\| x_i^M - x_j^M \right\|$ defines the distance between points in the M-dimensional space and Θ is the Heaviside function. Correlation dimension is to be estimated as a saturating value of the exponent for large enough M. In our experiments, as is typical of biological systems, the nonsaturating behaviour of $\nu(M)$ was observed. We suppose that this behaviour is related with the unavoidable presence of the random noise in heart rate data.

Therefore for calcullations of correlation dimension was used suggested in [5] modified Grassberger-Proccacia algorithm to eliminate random noise influence. The

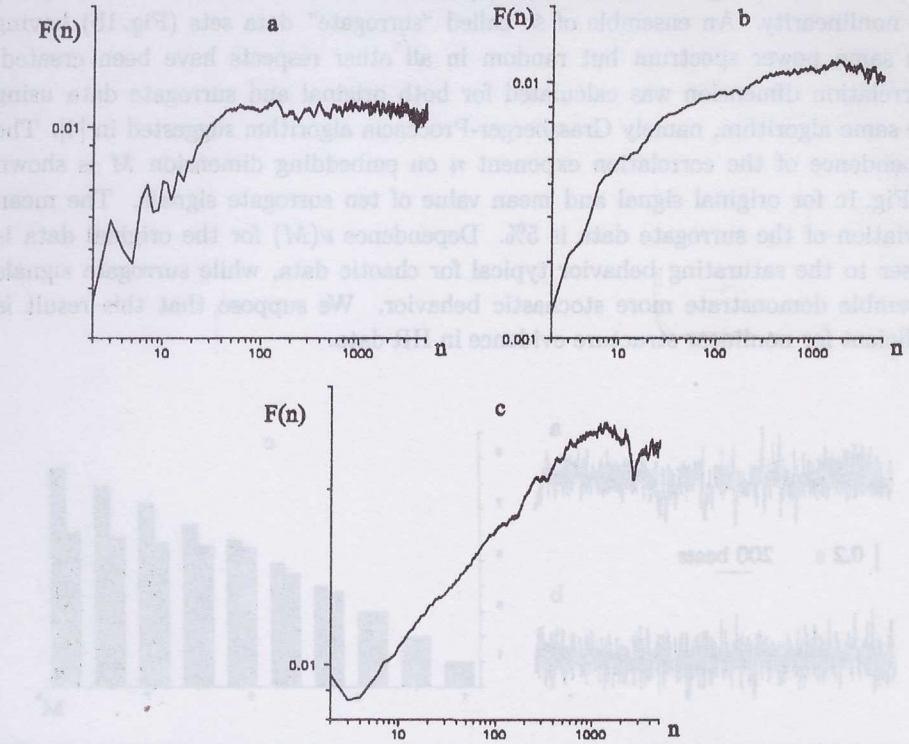

Fig. 2. Long range correlations for the HR in healthy adult subjects: a) normal, b) well trained sportsman, c) ischemic heart disease.

main idea of the algorithm for determining the correlation dimension from the noisy data suggested in [5] is to find the linear part of the plot ν vs M in the range of large values of M. This line is extended until it intersects the line $\nu(M) = M$. The needed correlation dimension of the underlying attractor is determined by the intersection point. This method is valid, however, if the slope of the function $\nu(M) = M$ is small enough. The delay τ is a free parameter in this method. The Takens theorem suggests that theoretically the choice of this parameter is not important. In practice, however, it is crucial to choose a good value of τ due to the noise and the short time series. It is shown that the most effective sampling frequency for biological signals is in the range of 100–500 Hz [1, 2].

Long-range correlations were calculated by means of fluctuation function $F(n)$ introduced in [6]. Function $F(n) = \langle (x_n - x_{n-N})^2 \rangle$ by the definition quantifies magnitude of the fluctuations over different time scales. They has shown significant differences over physiologically relevant time scales (200–3000 heart beats) in different investigated groups. In the case of CAD patients linear part in the log-log plot corresponding to the scale invariant power law behavior has the same exponent

in the range from the very small to the large time scales. In other cases change of behavior at about 100 heart beats is clearly seen. Scaling exponent estimated from the linear fit in the range of 2000-3000 heart beats varies from 0 for well trained subjects to 0.2 for CAD patients [7, 8].

Both above parameters characterize average system state during long period of time. Interesting for physiologists information about the local dynamical structure is lost in this analysis. Analysis of the return maps represents a possibility to obtain an informative picture of cardiac activity detected by short-range correlations in RR and SV data. For CAD patient with normal sinus rhythm return maps typically have random distribution of points, which is dependent on HR variability level and a period of the dominating HR waves. Reduction of HR variability and occurrence of some dysrhythmias, namely atrial fibrillation, premature beats, sino-atrial or atrioventricular blocks, lead to the simplification of system behavior, namely occurrence of some periodical structure in the return map [7]. An analysis of short-range correlation of successive RR intervals and stroke volume (SV) values was performed using Poincare maps in CAD patients having normal sinus rhythm or sinus rhythm with some dysrhythmias: premature beats (PB's), sino-atrial (SA) or atrioventricular (AV) blocks, episodes of parasystolia (Fig. 3).

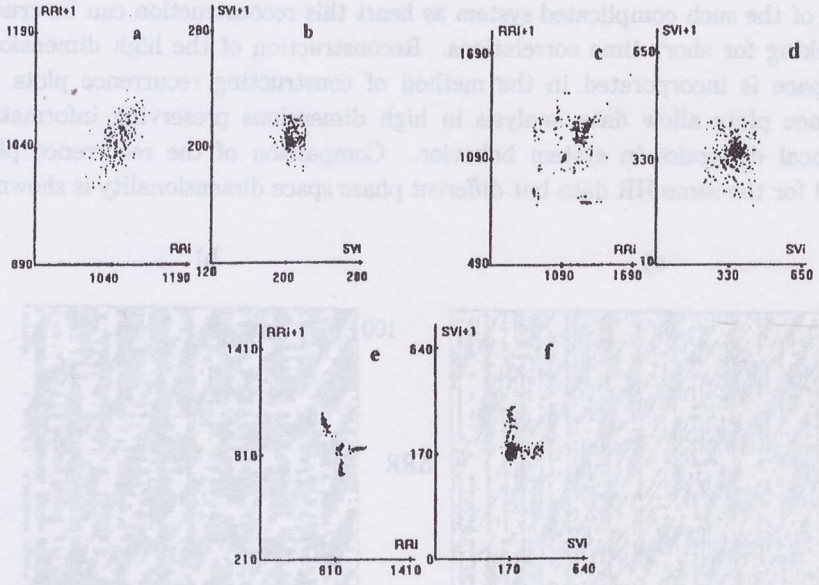

Fig. 3. Return maps of successive RR intervals and stroke volume records for: 1) IHD patient with normal sinus rhythm (a,b), 2) combined sinus rhythm, atrioventricular blocks and premature beats record (c,d), 3) sinus rhythm with ventricular PB's (parasystolia) with episodes of allorhythmias (e,f).

In the case of CAD patient with normal sinus rhythm, demonstrating prevalence of parasympathetic control (respiratory arrhythmia), Poincare mapings are ellipse-form cloud of points (Fig. 3a,b), which depends on the HR variability level and the

period of the dominating HR waves. Reduction of HR variability is followed by the changes in the shape of diagrams tending to the pattern of point.

In the case of HR disturbances particular specific patterns of mapings were obtained. Record of sinus rhythm with AV blocks and separate ventricular PB's (Fig. 3b) demonstrates quadrangular distribution, related to PB's, postextrasystolic cycles, and the cycles with AV blocks concentrating on the upper part of the Fig. 3b, while point at center, corresponds to reduced HR variability. Poincare mapping while ventricular PB's (parasystolia) with episodes of allorhythmias is present (Fig. 3c), has three separate elliptic clouds, related to normal sinus rhythm, preextrasystolic and post-extrasystolic intervals. Stroke volume values distribution (Fig. 3d) demonstrate three levels of hemodynamics, corresponding to sinus rhythm, preextrasystolic and postextrasystolic intervals.

We have expectations that return maps might be useful for quick detection of cardiac pathological events in permanent visual monitoring of patient's functional status.

Return maps can be considered as a method to present single variate experimental data in the more informative form. The essential component of the nonlinear dynamics methods is reconstruction of the high dimensional phase space. For the analysis of the such complicated system as heart this reconstruction can be crucial even looking for short time correlations. Reconstruction of the high dimensional phase space is incorporated in the method of constructing recurrence plots [9]. Recurrence plots allow data analysis in high dimensions preserving information about local dynamics in system behavior. Comparison of the recurrence plots obtained for the same HR data but different phase space dimensionality is shown in Fig. 4.

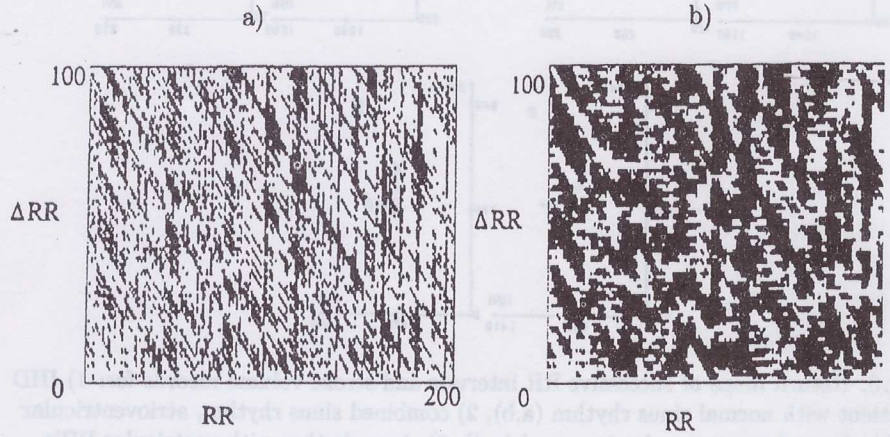

Fig. 4. Recurrence plot for RR intervals data in reconstructed phase space a) embedding dimension $M = 1$, b) $M = 5$.

Local periodical structure of the data hidden in one dimensional recurrence plot is more clear in higher dimensional plot. Observed periodical structure is caused

by dominant biological processes of the living organism. Changes in the structure of recurrence plots indicate changes in the state of system under investigation and have diagnostic features useful for physiology. As an example of such diagnostics can serve study of the heart activity during the all night sleep.

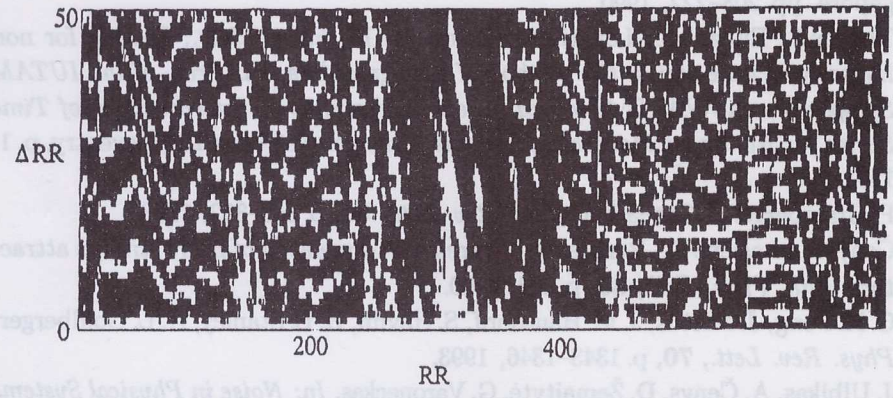

Fig. 5. Recurrence plot for $M = 5$ case of night sleep test data fragment with transition between two different sleep stages. White regions corresponds to the correlated sygnal.

It is well known that during sleep heart activity changes accordingly with stages of sleep. These changes are different for normal and pathological cases. Therefore dependencies of the dominant periodical structures in HR data during night sleep obtained from recurrence plots (Fig. 5) have clear diagnostic features.

CONCLUSIONS

Our investigations of heart rate data has shown, that correlation analysis based on nonlinear dynamics methods can be applied for cardiac pathology diagnostics. Our results also show that standard nonlinear dynamics methods without specific modifications can give spuriuos results. Therefore very careful analysis of particular biological data preceding investigation must be made.

Obtained results from calculation of quantitative nonlinear dynamics characteristics show their usefullness for description of state of biological system in general. As an example of long-range correlations of successive RR intervals might be used as quantitative characteristic for detection of cardiac pathology. Scaling exponent for fluctuation function $F(n)$ was obtained markedly different for normal and pathological situations, i. e. could show an increase in it's absolute value in relation to development of cardiac pathology.

From the other hand, features of local dynamics, which are very informative for physiologists, can be successfully visualized by simple return mapings. Recurrence plots represent another useful tool for diagnostics of changes in autonomic HR control due to cardiac pathology obtained from dominant periodical structures in HR data. They might be seen as very simple and convenient measures for preliminary indication of the cardiac abnormalities.

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