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TIME SERIES ANALYSIS OF ECG: A POSSIBILITY OF THE INITIAL DIAGNOSTICS

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The methods of nonlinear dynamics are applied to reveal the pathologies of patients with different heart failures. Our approach is based on the analysis of the correlation and embedding dimensions of the *RR*-intervals of ECGs. We demonstrate that these characteristics are quite convenient tools for the initial diagnosis. Advantages and disadvantages of the method are discussed.

Keywords: Correlation dimension; ECG; RR-intervals.

1. Introduction

Cardiovascular diseases (CVDs) are responsible for more than 4 million deaths per year, and so the investigations of physiological features of the cardiac function attract considerable interest [European Cardiovascular Disease Statistics, 2004]. A major group of CVDs refer to the disturbances of the normal cardiac rhythm (arrhythmias). It appears that some arrhythmias can be analyzed by the contemporary methods developed in the frameworks of nonlinear dynamics. These are mainly based on the analysis of electrocardiograms (ECGs) as time series. It is expected that these methods may help to provide an initial diagnosis and to determine in certain cases the type of the cardiac pathology.

Investigations of the heart rhythm disturbances have been carried out for more than 50 years. Nevertheless, only recently, new methods of nonlinear dynamics have found applications in the clinical practice [Kurths *et al.*, 1995; Peng *et al.*, 1995; Govindar *et al.*, 1998; Wessel *et al.*, 2000a; Wessel *et al.*, 2000b; Schulte-Frohlinde *et al.*, 2001; Janson *et al.*, 2002; Loskutov *et al.*, 2004; Loskutov *et al.*, 2005]. The basic goal of the present study is to reveal dynamical characteristics of ECG as a function of different physiological pathologies of the heart tissue and investigate its possible application in clinical practice.

In the medical practice, the normal palpitation is commonly described by so-called "normal sinus rhythm". However, in spite of this term the intervals between the heart beats perform certain fluctuations. Namely, even at rest a healthy heart has certain rhythm variations. Moreover, the exact periodic dependencies in the heart rhythm indicate the evidence of the severe cardiac pathologies [Goldberger & Rigney, 1988].

The extensive clinical investigations of 80's manifested that a normal heart rate exhibits some features, specific for deterministic chaos (see, e.g. [Goldberger, 1990; Goldberger *et al.*, 1990]). The results of subsequent studies have shown that dynamic characteristics found in the ECG analysis of healthy and cardiac patients were different [Peng *et al.*, 1995; Kurths *et al.*, 1995]. Moreover, the importance of the deterministic chaos in the heart rate has also been revealed (see, e.g. [Govindar *et al.*, 1998] and refs. cited therein). However, an alternative point of view is also supported (see, e.g. [Kanters *et al.*, 2002]). Hence, a lot of effort has been recently devoted to reveal the role of chaos in the development of heart diseases.

In the present paper, we analyze ECGs as time series of RR-intervals and study the complexity of the heart rate. We analyze correlations and embedding dimensions of the RR-sequences for a quite *large group of patients* with heart failures such as stenocardia, AV-block, cardiac infarction, etc. (see Sec. 4). The aim of our investigations is to obtain clear evidence that ECGs of patients with different pathologies may be quantitatively classified using the dimensional characteristics.

2. ECG as a Sequence of *RR*-Intervals

Physically, ECG is a record of an electric signal produced by a heart. In a normal state each peak of ECG (positive or negative) corresponds to the excitation or repolarization of the different parts of the cardiac tissue. The interval between the two neighboring peaks of R-waves is equal to the total cardiac cycle and is called RR-interval.

To analyze the heart rate variability (HRV), an ECG is represented in a form of a time series. Usually this time series is an array of N numbers, being certain values of a dynamical variable $x(t)$ taken after equal time intervals. In the application to the ECG analysis, there are two different ways of the time series formation: classical [Schuster, 1984; Mikhailov & Loskutov, 1995; Cutler & Kaplan, 1997] when the variable is measured after equal time intervals, and a series composed of the intervals between R-waves [Sauer, 1994, 1997; Racicot & Longtin, 1997]. Presently, we apply the second method. Let us explain it in more detail: Each R-peak of ECG appeared in time t_i is replaced by a single impulse, which is approximated by a Dirac delta function $\delta(t - t_i)$. Thus, the total ECG is replaced by the sequence of RR-intervals: $x(t) \to \sum_i \delta(t - t_i)$. Therefore, the desired time series $V(i)$ is formed by the values of intervals between the single pulses $RR(i)\colon RR_i = V(i)$, $V = (V(1), V(2), \ldots, V(N))$, where N is the total number of elements in the time series.

Note, that this method is widely used to analyze biological systems characterized by peak signals. Although such representation is not a classical sequence obtained via equal time intervals, it may be treated as a typical realization of some nonlinear system [Sauer, 1994]. Within this approach, it is possible not only to reveal latent regularities of the heart rate but also quantify characteristics of chaotic processes inherent for the initial ECG (e.g. to estimate the embedding dimension).

3. Dimension of ECG

It is known that an appearance of pathology in the cardiac tissue leads to certain changes in the ECG. As shown below, these changes can be recognized by the analysis of such quantitative characteristics of the attractor as the correlation dimension and the embedding dimension. As an attractor characteristic, the correlation dimension may be obtained from time series of RR-intervals of the ECG by the well-known method [Grassberger & Procaccia, 1983]. According to it, the reconstruction procedure of the phase space and the system attractor is reduced to the analysis of pseudoattractor. The time delay was chosen where the autocorrelation function of the series has its first zero.

The correlation dimension d and the embedding dimension m carries the information about the system complexity. However, we wish to stress that estimates of these characteristics may be correctly obtained on the physical assumption that the dynamical processes are statistically stationary, i.e. the considered system has already passed a transient state and reached the asymptotic regime where its properties are independent of the initial conditions. This also implies that the system parameters must remain constant. In addition to that, the reasonable estimates of d and m require about $O(N^2)$ operations: This method of the time series analysis loses its validity when a short sequence (less than 10^4 values) is addressed [Loskutov *et al.*, 2002]. Thus, to estimate correctly the embedding and the correlation dimensions, the following restrictions are to be taken into account: (i) the time series should be stationary [Schuster, 1984; Kennel, 1997; Ivanov *et al.*, 2002]; (ii) The sample length should not be less than $N_{\min} \approx 10^{d/2}$.

According to the first condition, the estimate of the HRV may be incorrect. However, for our analysis the exact value of the correlation dimension d is not of primary importance, since we need to find a clear-cut distinction between the ECG dimension d for patients with different diseases. For this formulation of the problem, it is sufficient to determine d for several fixed (quite large) values of the embedding dimension m. One can expect that at large m the dependence $d(m)$ should be different for various heart failures. To get more accurate results, we considered the *groups* of patients, that is, a statistical approach has been applied. The analysis has been carried out using the data obtained from a few to tens of ECGs. Then the results have been averaged. Such an approach allows to make a presumptive diagnosis (see Sec. 4).

To comment on the second restriction we note the use of mobile devices, such as Holter monitor, allows to record the ECG almost few days without interruption. This is quite sufficient to receive time series of RR-intervals consisting of more than 10^5 elements.

4. Analysis of Real Data

We have analyzed 159 sequences of RR-intervals obtained from ECGs of patients with different deviations in the cardiac rhythms. All the ECGs have been taken from the source of National Center for Research Resources (P41 RR13622) [Goldberger, 2000; PhysioNet, 2003]. This database is subdivided into groups of ECGs according to the patient's cardiac diseases. The age of patients and their gender have not been taken into account. The length of each time series was on average, 10^5 elements. To exclude random pulses (they always occur in contemporary mobile electrocardiographs) the chosen ECGs were specially processed, i.e. false pulses were filtered by standard methods. In accordance with them, we have eliminated the false peaks which were identified in the PhysioNet Data as artefacts.

After computer analysis of each ECG, the obtained values in each group were averaged. The results of the computed correlation dimension of ECGs for the values of the embedding dimension $m = 3$, $m = 4$, $m = 5$ with corresponding standard deviations are shown in Table 1.

One can see that the correlation dimension of the groups of patients with various cardiac pathologies differ from each other. However, this does not hold for all groups. For example, for a certain value of the embedding dimension, $m = 3$, the range of values of d may overlap. This happens for the third (patients with the rest angina and the cardiac vessel involvement) and the fourth (patients with the rest angina and myocardial infarction) groups, as well as for the first (patients with the cardiac vessel involvement of various extent) and the eighth (patients with mixed angina and cardiac vessel involvement) groups (see Table 1). Nevertheless, the diagnoses of the corresponding patients partly coincide, which explains the overlap in the correlation dimensions.

Table 1. 1. Patients with cardiac vessel diseases in various range (21 ECGs). 2. Patients with coronary artery bypass grafting and myocardial infarction (12 ECGs). 3. Patients with resting angina and cardiac vessel diseases (17 ECGs). 4. Patients with resting angina and myocardial infarction (9 ECGs). 5. Patients with congestive heart failure (21 ECGs). 6. Patients with resting angina and coronary artery involvement (13 ECGs). 7. Patients with effort angina and myocardial infarction (16 ECGs). 8. Patients with mixed angina and different vessel diseases (32 ECGs). 9. Patients with AV-block (6 ECGs). 10. Patients endured ventricular fibrillation (7 ECGs). 11. Patients with atrial flutter (18 ECGs).

Group of ECGs	d for $m = 3$	d for $m = 4$	d for $m = 5$
1	2.51 ± 0.04	3.12 ± 0.05	3.61 ± 0.1
2	2.13 ± 0.02	2.60 ± 0.03	2.78 ± 0.03
3	2.68 ± 0.04	3.29 ± 0.07	3.66 ± 0.08
4	2.74 ± 0.05	3.45 ± 0.06	3.89 ± 0.1
5	2.83 ± 0.03	3.70 ± 0.06	4.44 ± 0.09
6	2.57 ± 0.03	3.08 ± 0.08	3.78 ± 0.1
7	2.32 ± 0.03	2.81 ± 0.05	3.57 ± 0.1
8	2.53 ± 0.04	2.98 ± 0.05	3.75 ± 0.1
9	1.02 ± 0.03	1.36 ± 0.04	1.42 ± 0.06
10	2.98 ± 0.04	3.81 ± 0.06	4.23 ± 0.1
11	2.61 ± 0.03	3.19 ± 0.04	3.51 ± 0.08

With increasing embedding dimension ($m = 4$ and $m = 5$) the intervals of d for the same groups (3 and 4, 1 and 8) do not overlap any more. Increasing the dimension m it makes it possible to recognize the pathology group, i.e. with the further growth of the embedding dimension the correlation dimensions for each patient group demonstrate strong divergency. These results are shown in Fig. 1.

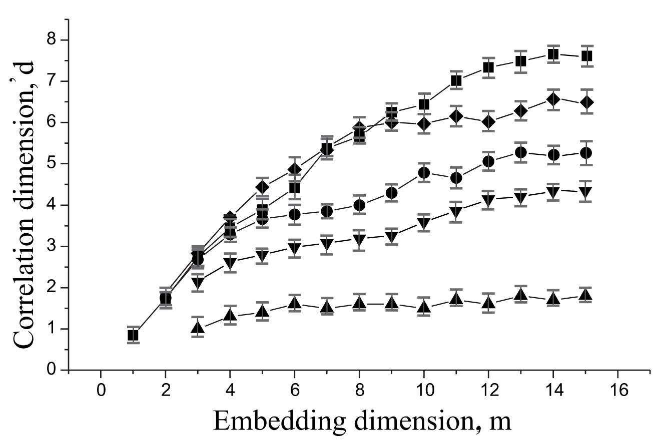

Fig. 1. The dependence of the correlation dimension of the patient ECG with different pathologies from the embedding dimension. ■ — resting angina and myocardial infarction, ♦ — congestive heart failure, • — resting angina and cardiac vessel diseases, ▼ — coronary artery bypass grafting and myocardial infarction, ▲ — AV-block.

They are supported also by the one factor analysis of variance [Altman, 1991] with the significance level of 0.05.

We can summarize the obtained results as follows. The correlation dimension of ECGs for various pathologies may be clearly discriminated for large values of the embedding dimension. This means that starting at some m it makes it possible to subdivide the patients into groups. Thus, we may come to the conclusion that, even despite the fact that we used the database where the age of patients and their gender have not been taken into account, methods of nonlinear dynamics can play a key role in the detection of certain cardiac diseases.

5. Concluding Remarks

In the present study we have analyzed the sequences of *RR*-intervals of ECGs obtained from patients, who suffer some cardiac diseases and time series corresponding to the normal cardiac rhythm of healthy persons. As a result of this analysis it has been shown that the dimensional characteristics used allow to resolve the inverse problem, that is, to divide patients into groups according to their cardiac diseases. The increase and/or decrease of the degree of chaos has been observed in the ECG according to the disease. We wish to stress that this conclusion has been made on the basis of the analysis of sufficiently long time series and a quite large number of patients from each group.

The use of dimensional characteristics of ECGs makes it possible to automatize the process of the initial diagnosis for patients with several cardiac pathologies. Solution of this and similar questions would allow us to find the boundary beyond which chaotic processes (that are inherent in the cardiac rhythm) do not already correspond to the healthy state but uniquely indicate to pathologies.

Finally, we would like to emphasize the following. It is well known that cardiac pathologies are not necessarily caused by the cardiovascular system dysfunction; they may also be a result of other diseases. This makes the investigation of so-called latent cardiac pathologies and indirect disturbances in the cardiac rhythms of a special importance. Usually it is not possible to detect such pathologies by the standard approaches. Application of nonlinear dynamical methods seems to be rather promising [Loskutov *et al.*, 2005].

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