ECG features characterizing the heart-brain interaction

Andrushchenko, Alexander, Institute of Space Investigations of Ukrainian Acad. Sci., 40, pr.Gluskova, Kiev, 252187, Ukraine.
Parkhomenko, Alexander, Ukrainian Institute of Cardiology, 5 Narodnogo Opolchenia St., Kiev, 252151, Ukraine.

Abstract

The problem of ECG analysis to find dynamical signatures of the heart-brain interaction is considered. Several methods are applied to study three groups of ECG signals: those of healthy people, patients after myocardial infarction (AMI) and animals without direct heart-brain interaction (WHBI). It is shown that there are ECG features allowing to distinguish statistically significantly the mentioned groups of ECG signals.

Introduction

It is well known [1,2] that the nature of the heart-brain interaction is very complex and different aspects regarding this topic should be studied. In particular, the systematic investigation of EEG and ECG signals is useful to receive features characterizing such an interaction. Here, several methods were applied to the analysis of three groups of ECG signals. The signals of healthy people (20 subjects), patients after myocardial infarction (AMI, 20 patients) and animals without direct heart-brain interaction (WHBI, 7 animals) were analyzed, respectively. The following parameters of the signals were studied:

1. The dynamics of signals, i.e., the deterministic chaotic (generated by a strange attractor) or stochastic (random) one.
2. The presence of ECG segments with different both statistical (the probability density) and dynamical (chaotic or stochastic) properties.
3. The spectral peculiarities based on values of the local Lyapunov exponents.

The dynamics of a signal (the point 1) was determined by a version of the nonlinear forecasting technique after embedding of the signal in a certain multidimensional space. The spectral peculiarities (the point 3) were received by the order-q spectral method after selecting ECG segments with approximately equal values of the local Lyapunov exponents. This method allows to detect periodicities which appear in segments rarely occurred.

In the following sections, we present the methods used and results received.

The dynamics of ECG signals

To study the dynamics of a signal, it is necessary to apply an appropriate numerical criterion. Recently, a few criteria were proposed for this purpose [3-6]. Here, we apply the method described in ref.[6]. The reason of this choice is based on features as follows:

- a coefficient characterizing the dynamics shows a clear distinction between the chaotic behaviour and the stochastic one;
- a procedure for calculating of this coefficient is quick enough.

Denote by $s(1), s(2), \ldots, s(N)$ the time points of some one-dimensional time series. Using the Takens' embedding procedure [5,8], we receive the sequence of vectors

$$\mathrm{x(j) = (s(j), s(j + L), \ldots, s(j + (E - 1)L),\ j = 1, \ldots, N - (E - 1)L.}$$

Here, the embedding dimension and the lag time are designated by E and L, respectively. The embedding parameters E and L are chosen by using the methods [14] or by minimizing a translation error considered below.

Let $x_1, x_2, \ldots, x_k$ be the k nearest neighbours of some point x_0. Next, designate by $\mathrm{y}_1, y_2, \ldots y_k$ the images of $x_1, x_2, \ldots, x_k$ after one time step [8]. The translation vector $\nu_{\mathrm{j}} = y_i - x_i$ and its average

$$\langle \nu \rangle = \frac{1}{k+1} \sum_{j=0}^{k} \nu_j$$

are used to calculate the translation error

$$e_{tr} = \frac{1}{k+1} \sum_{j=0}^{k} \frac{\| \nu_j - \langle \nu \rangle \|^2}{\| \langle \nu \rangle \|^2},$$

where the Euclidean length is designated by $\|.\|$. It was shown [6] that the translation error e_{tr} is greater than or equal to unit for the Gaussian noise. We also verified this inference for a strongly non-Gaussian noise with the K-distribution probability density [7]. At the same time, $e_{tr} \leq 0.1$ for the Henon attractor that is significantly less than the value of e_{tr} for the Gaussian noise. The same ranges of the translation error were received for other attractors, including the logistic map and the Lorenz system [8]. Thus, translation error is a "good" discriminator between the stochastic and deterministic time series. This inference is correct if the length of time series is not too small.

Non-parametric segmentation

Next, some statistical characteristics of ECG time series were studied to distinguish statistically significantly the mentioned groups of signals. Notice that the four first moments of the probability density (i.e., mean, variance, asymmetry, excess) were useless to reveal the statistically

significant difference between the signals from the groups. A regression simulation of the signals was also unsatisfactory. Then, segmentation properties [9,10] of ECG time series were investigated. This means that a time series is divided into some parts (segments) according to a certain criterion of the probability density.

The segmentation-based approach has earlier been applied to an analysis of heart rate variability ([10]). However, such an analysis does not take into account other significant characteristics of ECG signal. Therefore, we analyzed all time points in the considered signals by the segmentation-based approach [11]. The non-parametric segmentation algorithm [11] was chosen here since it has the advantages as follows. First, this algorithm is non-parametric without any constraining assumptions. Second, the dynamic programming method used here allows to resolve the corresponding minimization problem. Third, a simple procedure based on the probability density can be applied to classify the segments. At the same time, we believe that other algorithms of segmentation (in particular, based on the generalized likehood ratio) can also be used here.

Let the time series consists of K homogeneous segments. The term "homogenous" means that each segment can be characterized by a stationary random process with some constant (for this segment) function of the probability density. The statistical properties of the segments are changed abruptly in certain points which are bounds between the segments. These bounds are designated by $T_j, j = 1,\dots,K-1$; the length of j th segment is denoted by τ_j. Then the initial time series $s(1), s(2),\dots, s(N)$ can be presented as a sum of segments $(X_1,\dots,X_k)$, where $X_j = (s(T_{j-1}+1),\dots,s(T_j))$ and $T_j = T_{j-1} + \tau_j, (j = 1,\dots,K-1, T_0 = 0)$.

It is also assumed that a complete set of the probability densities of the segments represents a family of thrice continuously differentiable functions. These functions and their derivatives should be limited. Furthermore, the following condition is imposed for any function $p(s)$ of the probability density:

$$A_m(p) = \int_R p(s)ds < \infty, m = 1,2,3.$$

The estimation of the distance between the segments is carried out by

$$(1) \quad \rho_{j_1 j_2} = \rho_{j_1 j_2}\left(T_{j_1-1}, T_{j_1}, T_{j_2-1} T_{j_2}\right) = \int \left(p_{j_1}(s) - p_{j_2}(s)\right)^2 ds/2,$$

$$(2) \quad p_i(s) = (\tau i)^{-1} \sum_{t=T_i-1}^{T_i} \left|Hi\right|^{-1} K\left(Hi^{-1}(s - s(t)\right), i \in (j_1, j_2)$$

where p_i is the non-parametric probability density in the Rosenblatt-Parzen sense for the segment X_i. The Gaussian kernel $K(y)$ is defined by

$$K(y) = (2\pi)^2 \exp\left(-\frac{y^2}{2}\right)$$

The smoothing constant H_i is determined for every i th segment $H_i = b_i\left(T_i - T_{i-1}\right)^{-\alpha}$ where $\alpha > 0$ and $b_i > 0$. A value of the integral in (1) is estimated by the well-known Simpson formula.

The one-dimensional version of the algorithm [11] is applied here because all the ECG signals are scalar. The normalized distance between classes (segments) is denoted by

$r_{j_1 j_2} = r_{j_1 j_2}(T_{j_1-1}, T_{j_1}, T_{j_2-1}, T_{j_2})$.

Here, an estimate of the probability density computed by (2) for any time series assuming its homogeneity is used.

Notice that the quantity of segments K and the lengths of segments $\tau_1,\dots,\tau_{k-1}$ are unknown. At the same time, it is supposed that minimal and maximal values of these parameters are predetermined beforehand, i.e.,

$1 < K < 5, \tau_{\min} < \tau < \tau_{\max}, i = (1,\dots,K-1)$.

Hence, the functional to be minimized is expressed as follows

$$R = R(K, T_i) = (K-1)^{-1} \sum_{i=1}^{K-1} g_1(T_i - T_{i-1}, T_{i+1} - T_i)\, r_{i,i+1}(T_{i-1}, T_i, T_i, T_{i+1}).$$

The function $g_1(\tau, \tau')$ defines some two-dimensional probability density for the lengths of segments $\tau = T_i - T_{i-1}$ and $\tau' = T_{i+1} - T_i$.

Thus, the functional R represents the averaged with weights (over all $(K-1)$ changes of the probability density) the value of the distance between the segments. Hence, the evaluation of the quantity of segments K and the moments of changes T_i is obtained by the solution of the following optimization problem

$$R(K, T_i) \Rightarrow \max_{T_i} \max_{K},$$

where K falls into some admissible set A_k. Usually, A_k is a set of integers within the band lying from a minimum $K_{\min}$ to maximum $K_{\max}$, respectively. The length of the segment τ_i is also limited within the range $\tau_{\min} < \tau < \tau_{\max}$., where $\tau_{\min}$ and $\tau_{\max}$. are chosen taking into account the quantity and other features of data.

A maximization of R is carried out by the dynamic programming technique separately for every K from A_k.. Here, the conditions

$$T_{i-1} + \tau_{\min} \le T_i \le \min\{T_{i-1} + \tau_{\max}, N - (k-1)\,\tau_{\min}), i = 1, \ldots, K-1.$$

should be satisfied.

A classification of the received segments can be performed by methods described, for example, in [12]. Here, the following simple approach is applied. If we would like to obtain L classes from K segments, the $(K-L)$-step procedure is used. For the first step, the quantity of classes is assumed to be $L' = K$. Using the criterion of the minimal normalized distance between the segments

$$r_{kl}(T_{k-i}, T_k, T_{l-i}, T_l) \to \min_i, i \le k \le l \le L',$$

the numbers (k', l') of the most nearest segments are found. Then these two segments are unified in a new one segment with the number k'. Respectively, the quantity of classes to be considered is diminished to $L' = K-1$. This procedure is repeated up to the limit $L' = L$.
Then, the procedure of classification is completed and segments falling into every class are determined.

Hence, the segmentation parameters were evaluated for the analyzed groups of signals. Here, the computations were carried out for the number of segmentation points from one to four. If one segmentation point is considered, then both the position of this point and the normalized distance (ND) between the segments were taken into account to distinguish the groups. Since the size of registered ECG data is too large to apply the segmentation procedure directly, three values of N were applied: N =300, 500 and 1000. To increase the robustness of the procedure, the obtained parameters were estimated for 10 consecutive intervals, where each interval has N points, with the following averaging.

In the case when the number of segmentation points is larger than one, the following parameters were taken into account:

- the position of segmentation points;
- two minimal values of ND between the nearest (according to ND) segments;
- the numbers of segments unified into the first and second class, respectively;
- the averaged ND between the classes.

Thus, the most significant parameters of the segmentation procedure were analyzed to find the differences between the groups.

The order-q power spectrum

It is known that features of the ECG periodicities can be useful to characterize some heart abnormalities. For example, the spectral parameters of heart rate variability (HRV) and spectral-temporal analysis of signal-averaged ECG (STA) are applied for this purpose. However, the conventional spectral parameters (including those of HRV and STA) were not efficient enough in our situation. Notice also that the mentioned spectral parameters are characteristics of the whole signal or the most typical cardiac complex. At the same time, there is the possibility that some cardiac disorders cause periodical components in ECG segments rarely occurred. The number of the segments and their bounds are not known beforehand.

Recently, a new method called the order-q power spectrum was proposed to detect the order-q periodicities in time series [13]. These periodicities appear in segments with certain characteristics of the nonlinear dynamics. Here, we give a simplified version of the method basing on the fact that different segments of an ECG signal have, on the whole, different informational features. These features can be purely statistical (e.g., mean, variance, probability density) or dynamical. The latter are intended to describe the deterministic dynamics of the signal in a certain phase space.

Since the periodicities lead to the deterministic dynamics, we can select appropriate segments based on characteristics of this dynamics. Here, values of the local Lyapunov exponents were used. It should also be noticed that the local Lyapunov exponents are essential characteristics of the time behaviour of the signal considered [5,8]. In particular, a nonlinear local predictability can be evaluated by these characteristics.

The values of the local Lyapunov exponents are computed for each point of a time series. Then, the whole time series is divided into segments with different averaged magnitudes of the local Lyapunov exponents. Next, new components are received by joining of segments with approximately equal these magnitudes. The components are analyzed by the conventional spectral method. The following parameters of the this nonlinear method were estimated:

1. The amplitude of the main (highest) spectral peak;
2. The position (i.e., the frequency value) of this peak.

Here, we describe shortly the method allowing to find the order-q periodicities [13]. Let, as earlier, we have one-dimensional time series $s(1), s(2), \ldots, s(N)$ which is divided into k segments. Each segment contains n points. The order-q power spectrum $I_q(\omega)$ is calculated by selecting of the segments with equal averaged values Λ_n of the local Lyapunov exponents λ_i

$$I_q(\omega) = \lim_{n\to\infty} \frac{\left\langle I(\omega,n)\delta(\Lambda(q)-\Lambda_n)\right\rangle}{\left\langle \delta(\Lambda(q)-\Lambda_n)\right\rangle} = \lim_{n\to\infty} \frac{\left\langle I(\omega,n)\exp\left(qn\,\Lambda_n\right)\right\rangle}{\left\langle \exp\left(qn\,\Lambda_n\right)\right\rangle}$$

Here, $\langle \cdots \rangle$ designates the time average over all the segments. The power spectrum $I(\omega,n)$ for every selected segment is calculated in the conventional way

$$I(\omega,n) = \left| \frac{1}{\sqrt{n}} \sum_{l=0}^{n-1} s(l)\exp(il\omega) \right|^2$$

Notice that the values $\lambda_i, i = 0,1,2,\ldots$ are estimated along the trajectory in phase space and they are taken into account as a new time series.

The groups of signals were compared by the spectral parameters obtained from the components chosen, as mentioned, at the same averaged values of the local Lyapunov exponents.

Summary

We have a few findings in the present study. In particular, it was found that the WHBI signals are deterministic while the other signals have, as a rule, the stochastic or intermediate dynamics. The ECG time series of patients after myocardial infarction are more deterministic (i.e., close to the WHBI signals) than those of the healthy people ($p<0.05$ by the Mann-Whitney nonparametric test). The segments with different (in the statistically significant sense) probability density functions were not received for all the signals. However, the groups were discerned by the distance between the probability densities of the segments ($p<0.05$). Using the order-q method, specific spectral components were found for each of the three groups of signals ($p<0.01$). Thus, there are the ECG characteristics allowing to distinguish statistically significantly the ECG signals recorded without the heart-brain interaction. According to values of these characteristics, the signals for the patients after myocardial infarction are closer to the WHBI signals than those of the healthy people.

References

[1] Carpeggiani C et al. .Nonlinear dynamics of heart rate in normal subjects. European Heart Journal. 1993, v.14, Abstract Supplement. p.428

[2] Goldberger AL Fractal mechanisms in the electrophysiology of the heart. IEEE Eng. Med. Biol. Mag. 1992, v.11, pp.47-49

[3] Kaplan DT and Glass L Direct test for determinism in a time series. Phys. Rev. Lett. 1992, v.68, pp.427-430

[4] Kennel Mb and Isabelle S Method to distinguish possible chaos from colored noise and to determine embedding parameters. Phys. Rev. A 1992, v.46, pp.3111-3116

[5] Abarbanel HDD et al. The analysis of observed chaotic data in physical systems. Reviews of Modern Physics, 1993, v.65, pp.1331-1392

[6] Wayland R et al. Recognizing determinism in a time series. Phys. Rev. Lett., 1993, v.70, pp.580-583

[7] Jakeman E On the statistics of K-distributed noise. J. Phys. A, 1980, v. 13, pp.31-36

[8] Shuster HG Deterministic chaos. Physic-Verlag, Weinheim, 1989

[9] Willsky AS Survey of design methods for failure detection in dynamic systems. Automatica, 1976, v.12, pp.601-611

[10] Basseville M and Benveniste A (editors) Detection of abrupt changes in signals and dynamical systems. Lecture notes in control and information sciences, 77. Springer-Verlag, Berlin, Heidelberg, New York, Tokyo, 1986.

[11] Melnikova YeK and Kharin YuS The detection of multiple changes and classification of time series by statistical estimates of distances between classes. Automatica and Telemekhanica
(Autom. Remote Control, USA) 1991, v.12, pp.76-84

[12] Hunt EB Artificial intelligence. Academic press, New York, San Francisco, London, 1975

[13] Shibata H and Ishizaki R Periodicity in trajectories of chaotic systems in phase space. Physica A, 1993, v.197, pp.130-143