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Age-related alterations of relaxation processes and non-Markov effects in stochastic dynamics of R–R intervals variability from human ECGs

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Abstract

In this paper, we consider the age-related alterations of heart rate variability on the basis of the study of non-Markovian effects. The age dynamics of relaxation processes is quantitatively described by means of local relaxation parameters, calculated by the specific localization procedure. We offer a quantitative informational measure of non-Markovity to evaluate the change of statistical effects of memory. Local relaxation parameters for young and elderly people differ by 3.3 times, and quantitative measures of non-Markovity differ by 4.2 times. The comparison of quantitative parameters allows to draw conclusions about the reduction of relaxation rate with ageing and the higher degree of the Markovity of heart rate variability of elderly people.
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1. Introduction

The ageing of a human organism has been in the focus of attention in physics of live systems over the past years. One of the most significant systems of vital activity of a human body is its cardiovascular system. Today there are a number of scientific studies on the problems of biological ageing of the cardiovascular human system. The latter is extremely sensitive to age-related as well as pathological changes in a human organism. Thus not only physiologists, biologists and physicians have been involved in this studies but also experts from other natural-science areas. Conditions of a human heart are estimated by means of various parameters. Thus heart rate variability (HRV) represents one of the most frequently used parameters, in cardiology. Nowadays there are different methods of studying HRV dynamics. In recent years [1], fluctuations of heartbeat dynamics have been studied by means of several methods derived from nonlinear dynamics and statistical physics, such as detrended fluctuation analysis (DFA) [2,3], spectral analysis [4], entropy [5–7], correlation dimension [8]. In paper [9] authors illustrate the problems related to the physiological signal analysis with representative examples of human heartbeat dynamics under healthy and pathological conditions which is based on two methods: power spectrum and detrended fluctuation analysis. In this paper different characteristics of heartbeat: $1/f$ fluctuations, long-range anticorrelations (monofractal analysis), self-similar cascades, multifractality and nonlinearity are considered. By means of a wavelet-based multifractal formalism it is shown that healthy human heartbeat dynamics exhibits higher complexity which is characterized by a broad multifractal spectrum. In paper [10] multiresolution wavelet analysis has been used to study the HRV in a patient with different pathological conditions. Noise effects of abnormal heartbeats were considered in paper [11]. The correlation exceptions of heartbeat dynamics of different sleep stages often have been researched lately. In papers [12,13] correlation properties of the magnitude and the sign of increments in the time intervals between successive heartbeats during a light sleep, a deep sleep, a rapid eye movement sleep were discovered by means of the detrended fluctuation analysis. Multiscaled randomness [14], multifractal analysis [15], simulation by nonlinear oscillators [16], fractal approach based on scaling of a frequency spectrum on power law $1/\omega^{\alpha}$ [17], quantitative analysis [18] are also used to analyze HRV. The change of correlations and statistical memory effects is one of the most important questions [19] in HRV dynamics observed with ageing [1,4].

Among existing methods of researching HRV one can differentiate the methods of estimating HRV in a time area, spectral methods of estimating HRV in a frequency area, as well as nonlinear methods. The last group of methods has proved to be a powerful means to study various complex systems and has brought about significant achievements in processing biological and medical data. In recent years universal methods of statistical physics have been more often used in medicine and biology. The methods of statistical physics which have been used to research real complex systems [20–25], in the field of cardiology reveal essentially new opportunities for the analysis, diagnostics and forecasting the processes of biological ageing and diseases

of a human heart. They disclose dynamic features of HRV, latent for classical medical methods of research.

In this paper, we offer a new method of study of the problems of ageing of a human heart activity, based on our theory of discrete non-Markov processes [20]. This theory has already found practical application in cardiology [21], neurophysiology [22,23], the study of locomotor and sensomotor activity [23], epidemiology [24] and seismology [25].

2. Basic concepts and definition of the statistical theory of nonstationary discrete non-Markov processes in complex systems

The obtained data were processed by means of the above declared technique. We use the results of our recent theory of discrete non-Markov random processes for the quantitative description of Markovian and non-Markovian components in stochastic alteration of the registered data. The set of three memory functions was calculated for each sequence of the data. Frequency power spectra for each of these functions are obtained by using the fast Fourier transform. For a more detailed analysis of the properties of the system we also consider the frequency spectrum of the first three points of the statistical spectrum of the non-Markovity parameter. The spectrum of the non-Markovity parameter was introduced earlier in the following articles [20,21,25]. In this study we use the frequency spectrum of the non-Markovity parameter:

$$\varepsilon_i(\omega) = \left\{ \frac{\mu_{i-1}(\omega)}{\mu_i(\omega)} \right\}^{1/2}, \qquad \mu_i(\omega) = \left| \int_0^\infty \mathrm{d}t\, M_i(t)\cos(\omega t) \right|^2 = \left| \sum_{j=0}^{N-1} M_i(t_j)\cos(\omega t_j) \right|^2,$$

here $i = 1, 2, 3 \ldots$ is the number of the relaxation level, $\mu_i(\omega)$ is the Fourier-transform and a power spectrum of the ith level memory function $M_i(t)$ (see Eq. (1)). The parameters $\varepsilon_i(\omega)$ allow to receive the quantitative estimation of long-term memory effects in the experimental time series of the data as shown in Ref. [26]. From the physical point of view the parameter $\varepsilon_i(\omega)$ allow to mark out the three most important cases [26]. Markov and completely randomized processes correspond to values $\varepsilon \to \infty$, quasi-Markov processes (memory effects can be noticed there) correspond to values $\varepsilon > 1$. The limiting case with $\varepsilon \sim 1$ concerns the situation with non-Markov processes, i.e., processes, where there is long-range memory.

In early works [20,21,25] we came to the following chain of connected non-Markov finite-difference kinetic equations ($t = m\tau$):

$$\frac{\Delta M_n(t)}{\Delta t} = \lambda_{n+1} M_n(t) - \tau \Lambda_{n+1} \sum_{j=0}^{m-1} M_{n+1}(j\tau) M_n(t - j\tau). \tag{1}$$

Here parameters λ_{n+1} represent eigenvalues of the Liouville's quasioperator. The relaxation parameters of Λ_{n+1} are determined as follows:

$$\lambda_{n+1} = i\frac{\langle \mathbf{W}_n \hat{L} \mathbf{W}_n \rangle}{\langle |\mathbf{W}_n|^2 \rangle}, \quad \Lambda_n = i\frac{\langle \mathbf{W}_{n-1} \hat{L} \mathbf{W}_n \rangle}{\langle |\mathbf{W}_{n-1}|^2 \rangle}. \tag{2}$$

The zero-order memory function $M_0(t)$ in Eq. (1):

$$M_0(t) = a(t) = \frac{\langle \mathbf{A}_k^0(0)\mathbf{A}_{m+k}^m(t)\rangle}{\langle |\mathbf{A}_k^0(0)|^2\rangle}, \quad t = m\tau ,$$

$$\mathbf{A}_k^0(0) = (\delta x_0, \delta x_1, \delta x_2, \ldots, \delta x_{k-1}) ,$$

$$\mathbf{A}_{m+k}^m(t) = \{\delta x_m, \delta x_{m+1}, \delta x_{m+2}, \ldots, \delta x_{m+k-1}\} ,$$

describes statistical memory in complex systems with a discrete time ($\mathbf{A}_k^0(0)$ and $\mathbf{A}_{m+k}^m(t)$ are vectors of the initial and final states of the studied system). In paper [20] we have received the recurrent formula on the basis of Gram–Schmidt orthogonalization procedure, in which the senior dynamic variable $\mathbf{W}_n = \mathbf{W}_n(t)$ is connected with the junior one in the following way:

$$\mathbf{W}_0 = \mathbf{A}_k^0(0), \quad \mathbf{W}_1 = \{i\hat{L} - \lambda_1\}\mathbf{W}_0, \ldots ,$$

$$\mathbf{W}_n = \{i\hat{L} - \lambda_{n-1}\}\mathbf{W}_{n-1} + \Lambda_{n-1}\mathbf{W}_{n-2} + \ldots, \quad n > 1 . \tag{3}$$

The initial time correlation function (TCF) $a(t)$ and the set of discrete memory functions $M_n(t)$ in Eq. (1) are important for further consideration. The first three equations of this chain ($t = m\tau$ is a discrete time) can be presented as follows:

$$\frac{\Delta a(t)}{\Delta t} = -\tau\Lambda_1 \sum_{j=0}^{m-1} M_1(j\tau)a(t - j\tau) + \lambda_1 a(t) ,$$

$$\frac{\Delta M_1(t)}{\Delta t} = -\tau\Lambda_2 \sum_{j=0}^{m-1} M_2(j\tau)M_1(t - j\tau) + \lambda_2 M_1(t) ,$$

$$\frac{\Delta M_2(t)}{\Delta t} = -\tau\Lambda_3 \sum_{j=0}^{m-1} M_3(j\tau)M_2(t - j\tau) + \lambda_3 M_2(t) . \tag{4}$$

This system of finite-difference Eqs. (1), (4) is a discrete analogue of the well-known chain of kinetic Zwanzig'–Mori's equations. The latter plays the fundamental role in modern statistical physics of non-equilibrium phenomena with a continuous time. It is necessary to note that the chain of Zwanzig'–Mori's equations is valid only for quantum and classical Hamiltonian systems with a continuous time. The chain of finite-difference kinetic Eqs. (1), (4) is valid for complex systems, in which there is no Hamiltonian, the time is discrete, and there are no exact equations of motion. However, "dynamics" and "motion" in real complex systems undoubtedly exist and can be registered in the experiment. The first three equations in the chain (4) form a basis for the quasihydrodynamic description of stochastic discrete processes in complex systems. The application of Eq. (1) opens up new possibilities in the detailed analysis of the statistical properties of correlations in complex systems. The existence of finite-difference Eqs. (1), (4)

allows to evaluate unknown memory functions (similarly time correlation functions) directly from the experimental data.

Let us determine the experimental relaxation time τ_E by the equation:

$$\tau_E = \Delta t \sum_{j=1}^{N} a(t_j) \,. \tag{5}$$

Using the experimental data now we can define the relaxation time of the studied system. Further we can compare the experimental time τ_E with the theoretical one. The theoretical relaxation time τ_E (where $i = 1, 2, 3, \ldots$, is the number of approximation) can be determined on the basis of Zwanzig'–Mori's equations for various correlation approximations. For the first age group (young people) better accordance between the experimental and theoretical times is gained in the sixth correlation approximation: $M_3(t) = M_1(t)$ (see Table 1). This one shows the presence of long-range memory in the considered system. For the examined group of elderly persons better accordance of relaxation times is received in the first correlation approximation $M_1(t) = a(t)$ (see Table 1). It indicates to the existence of short-range memory in this group (Table 2).

Using the Laplace transform on the first three Zwanzig'–Mori's equations, we shall receive:

$$s\tilde{a}(s) - 1 = \lambda_1 \tilde{a}(s) - \Lambda_1 \tilde{a}(s)\tilde{M}_1(s) \,,$$
$$s\tilde{M}_1(s) - 1 = \lambda_2 \tilde{M}_1(s) - \Lambda_2 \tilde{M}_1(s)\tilde{M}_2(s) \,,$$
$$s\tilde{M}_2(s) - 1 = \lambda_3 \tilde{M}_2(s) - \Lambda_3 \tilde{M}_2(s)\tilde{M}_3(s) \,.$$

One can solve this system by means of various approximations. For the approximation $M_1(t) = a(t)$ (the first approximation in Table 1) we shall receive:

$$\tilde{a}(s) = \frac{-(s - \lambda_1) + \sqrt{(s - \lambda_1)^2 + 4\Lambda_1^2}}{2\Lambda_1} \,,$$

$$\tau_1 = \lim_{s \to 0} \tilde{a}(s) = \frac{\lambda_1 + \sqrt{\lambda_1^2 + 4\Lambda_1^2}}{2\Lambda_1} \,.$$

Table 1
The experimental τ_E and theoretical τ_i $(i = 1, \ldots, 6)$ relaxation times for different age groups

Age	τ_E	$\tau_1(M_1(t) = a(t))$	$\tau_2(M_2(t) = M_1(t))$	$\tau_3(M_3(t) = M_2(t))$	$\tau_4(M_2(t) = a(t))$	$\tau_5(M_3(t) = a(t))$	$\tau_6(M_3(t) = M_1(t))$
Young	0.126	0.987	1.171	1.172	1.188	1.219	0.211
Old	0.147	0.260	7.262	6.864	0.789	5.440	0.045

Table 2
Some kinetic and relaxation parameters (absolute values) for young and elderly people, calculated from our theory

Age	Young	Old	Young	Old	Young	Old	Young	Old	Young	Old
Parameter	$\lambda_1(\tau^{-1})$		$\lambda_2(\tau^{-1})$		$\lambda_3(\tau^{-1})$		$\Lambda_1(\tau^{-2})$		$\Lambda_2(\tau^{-2})$	
$\langle A \rangle$	0.4551	0.1384	0.0490	1.1021	1.009	1.004	0.083	0.048	0.083	0.107
σ^2	0.016	0.003	0.004	0.010	3×10^{-4}	5×10^{-4}	0.004	0.001	0.004	0.011
σ	0.128	0.054	0.060	0.101	0.018	0.024	0.063	0.036	0.062	0.107

For the approximation $M_3(t) = M_1(t)$ (the sixth approximation in Table 1) we shall find:

$$\tilde{a}(s) = \frac{1}{\Lambda_1 \tilde{M}_1(s) + s - \lambda_1}$$

$$= \frac{2\Lambda_3(s-\lambda_2)}{2\Lambda_3(s-\lambda_2)(s-\lambda_1) - \Lambda_1(\Lambda_2 + (s-\lambda_2)(s-\lambda_3) - \Lambda_3) + \Lambda_1\sqrt{(\Lambda_2 + (s-\lambda_2)(s-\lambda_3) - \Lambda_3)^2 + 4\Lambda_3(s-\lambda_2)(s-\lambda_3)}} ,$$

$$\tau_6 = \lim_{s \to 0} \tilde{a}(s) = \frac{2\lambda_1\Lambda_3}{\Lambda_1(\Lambda_2 + \lambda_2\lambda_3 - \Lambda_3) - 2\lambda_1\lambda_2\lambda_3 - \Lambda_1\sqrt{(\Lambda_2 + \lambda_2\lambda_3 - \Lambda_3)^2 + 4\lambda_2\lambda_3\Lambda_3}} .$$

In Table 1 we show the experimental times of relaxation τ_E (see Eq. (5)) and theoretical times of relaxation τ_i for different age groups.

3. Experimental data

We used the time series of R–R intervals in young and elderly subjects as the experimental data [4]. Two groups of healthy human subjects: 10 young (mean age 27 yr, range 21–34 yr) and 10 elderly (mean age 74 yr, range 68–81 yr), participated in this study. Each group consisted of five women and five men. All subjects provided written informed consent and underwent a screening history, physical examination, routine blood count and biochemical tests, electrocardiogram, and exercise tolerance test. Only healthy, nonsmoking subjects with normal exercise tolerance tests, without any medical problems, and being on no medication were admitted to the study.

All subjects remained in an inactive state in sinus rhythm while watching the movie "Fantasia" (Disney) to maintain wakefulness. Each heartbeat was annotated by means of an automated arrhythmia detection algorithm, and each beat annotation was verified by visual inspection. The R–R interval (interbeat interval) of time series for each subject was then computed [4].

4. Discussion of the results

The basic outcomes are submitted in this section. Further the appropriate analysis of the experimental data will be carried out both for young and old people. Two new

qualitative procedures of the appropriate analysis have been used. The procedure of the window-time behavior shows great oscillations of an R–R interval for the power spectra of memory functions with respiratory arrhythmia. The calculation of the local relaxation parameters is carried out by means of the procedure of time localization. The decrease of the relaxation rate in ageing people is indicated through the time dependence of the localized relaxation parameters. The quantitative assessment of non-Markovity effects of HRV is carried out by means of a special measure.

4.1. Study of age-related alterations of HRV

Further we submitted figures for one young and one old person. The figures reflect a general pattern of the group. Below we show the analysis which describes the experimental data for the first and second group.

In Fig. 1 we have presented the time series of the first four dynamic orthogonal variables W_i, where $i = 0, \ldots, 3$ for young (Figs. 1a–d) and elderly (Figs. 1e–h) people. The time series of the elderly people differ in greater amplitude and
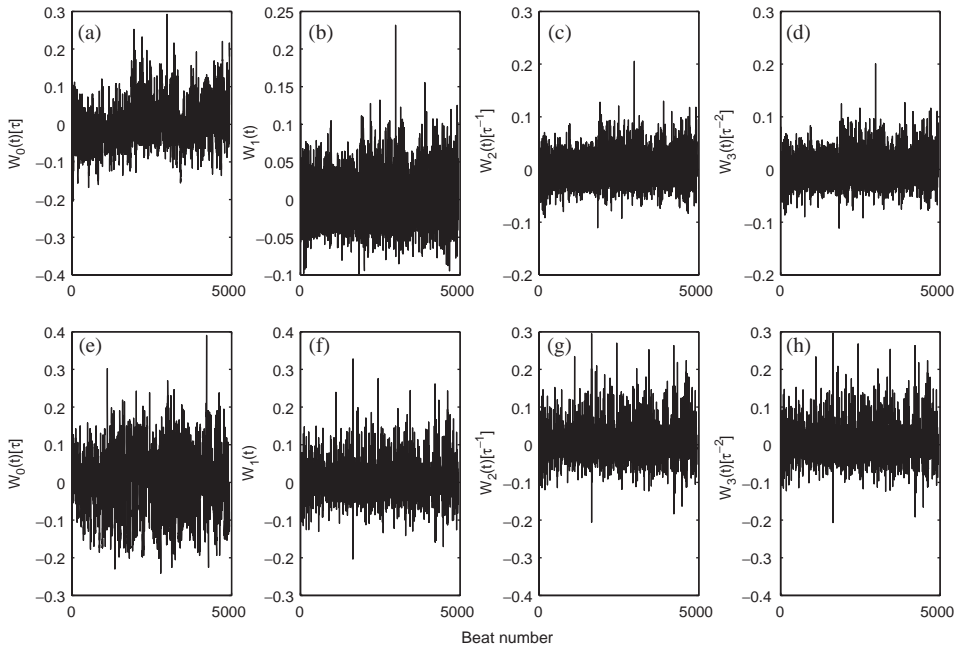

Fig. 1. The time series of the first four dynamic orthogonal variables W_i, where $i = 0, \ldots, 3$ for the young (a–d) and the elderly persons (e–h). The time series of the elderly person is accompanied by more significant fluctuations of an R–R interval. The time series of elderly person is characterized by greater frequency of occurrence of significant fluctuations. It shows higher degree of Markovity of the fluctuations of an R–R interval for the elderly person.

frequency of fluctuations of an R–R interval. The scattering interval of the oscillations of an R–R interval for young people constitutes (0.83τ–1.18τ, where $\tau = 1.0244$ s, τ-time of discretization). The variability of an R–R interval in elderly people changes within the limit of (0.92τ–1.5τ, where $\tau = 1.062$ s) for the initial signal. The frequency of fluctuations of an R–R interval in elderly people is greater than in young people. The normal cardiac activity of elderly people is accompanied by more randomized fluctuations of an R–R interval.

In Fig. 2 we have presented the phase portraits for the variability of an R–R interval in young and elderly people on six plane projections of the first four dynamic orthogonal variables. The phase clouds of the young and elderly people are symmetric concerning the origin of coordinates frame. The phase clouds have a centered nucleus. The nucleus encloses some points, speckled on the perimeter. The phase points for elderly people have a 2–3 times greater interval of a scattering, due to the presence of more appreciable oscillations of an R–R interval.
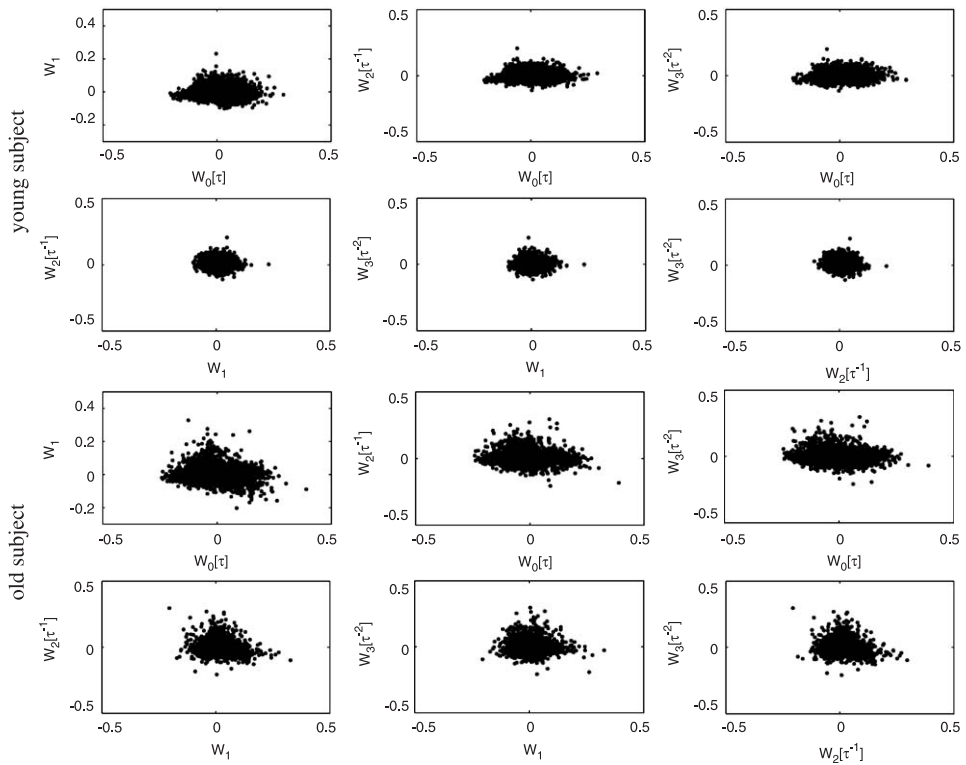

Fig. 2. The phase portraits of variability of an R–R interval on six plane projections of various combinations W_i, W_j for young and elderly people. The phase clouds of the young man are more compressed towards the center of coordinates system. Around the centralized nucleus of the phase clouds for the elderly person, separate points are scattered. The interval of their disorder 2–3 times exceeds the areas of disorder of the phase points for the young man.

In Fig. 3 we have presented the power spectra of the initial TCF $\mu_0(\omega)$ (Fig. 3a) and the first three memory functions of younger orders $\mu_i(\omega)$ (where $i = 1, 2, 3$) (Figs. 3b–d) for young and elderly people. The figures are submitted on a log–log scale. The power spectrum of the initial TCF for the elderly person differs in smaller dynamic fractures in the area of low frequencies. It is possible to find dynamic splashes (dynamic peaks) on all figures in the area of frequencies $(0.2\,\mathrm{f.u.} < \omega < 0.5\,\mathrm{f.u.}$, where $1\,\mathrm{f.u.} = 1/\tau)$, in particular. These dynamic peaks appear due to respiratory arrhythmia. The given dynamic splashes remind of the well known shape of the Suyumbike Tower [21]. The increase of the power spectrum on these frequencies reflects age-physiological changes. Ageing people develop a shift of these dynamic peaks in the range of high frequencies. The dynamic peaks, which relate to the respiratory arrhythmia of the young man, are discovered within the frequency interval of $0.25\,\mathrm{f.u.} < \omega < 0.45\,\mathrm{f.u.}$ These dynamic splashes of the elderly person are in the range of $0.4\,\mathrm{f.u.} < \omega < 0.55\,\mathrm{f.u.}$ The specific arrhythmia of cardiac activity at respiration accounts for this conclusion. This frequency (at respiratory arrhythmia) in elderly persons is higher than in young ones.
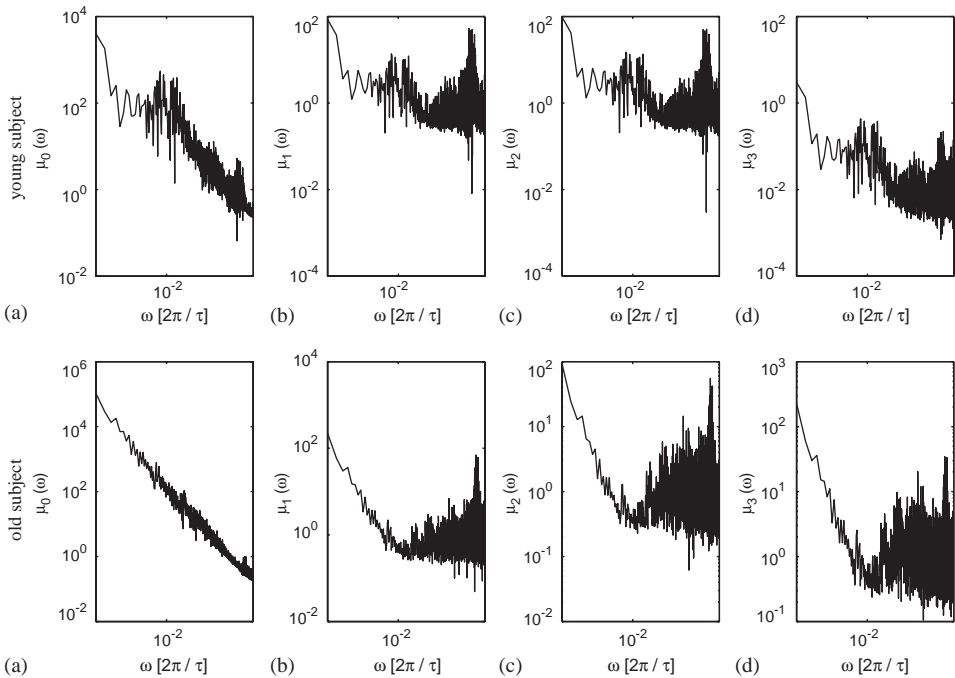

Fig. 3. The power spectra of the initial TCF (a) and the first three memory functions (b–d) for the young and elderly persons. The power spectra of the initial TCF of the elderly person differs in smaller dynamic breaks in the field of low frequencies. In all the power spectra the dynamic splashes (peaks) are found in the field of high frequencies, which is connected with respiratory arrhythmia. These dynamic peaks of the elderly person are shifted in the area of higher frequencies. It testifies to the increase in frequency of cardiac reductions at breath that comes with ageing.

The procedure construction of the window-time behavior of the power spectra of memory functions leads to the similar conclusion. The similar procedure allows to consider in detail any dynamic regularities originating in the power spectra of the memory functions. The idea of this procedure consists in the following [23]. Originally it is necessary to determine the optimal length of the sample. When the length of the sample is small, the "accumulated" information will be insufficient for carrying out a qualitative correlation analysis due to gross errors and the influence of noise effects. When the length of the sampling is large the necessary "sensitivity" weakens. The analysis of samples of different lengths shows, that the optimal length for this procedure constitutes $2^8 = 256$ points. From the initial array of the experimental data we take 256 initial points. We receive the first window of 256 points. Then we build a memory function power spectrum for this sample and take the next window of 256 points (from 257 to 512). Then we build the power spectrum of the memory function. This procedure is carried out repeatedly up to the end of the sampling of the experimental data. In Fig. 4 the time-window behavior of the first memory function $\mu_1(\omega)$ in young and elderly people is submitted. The
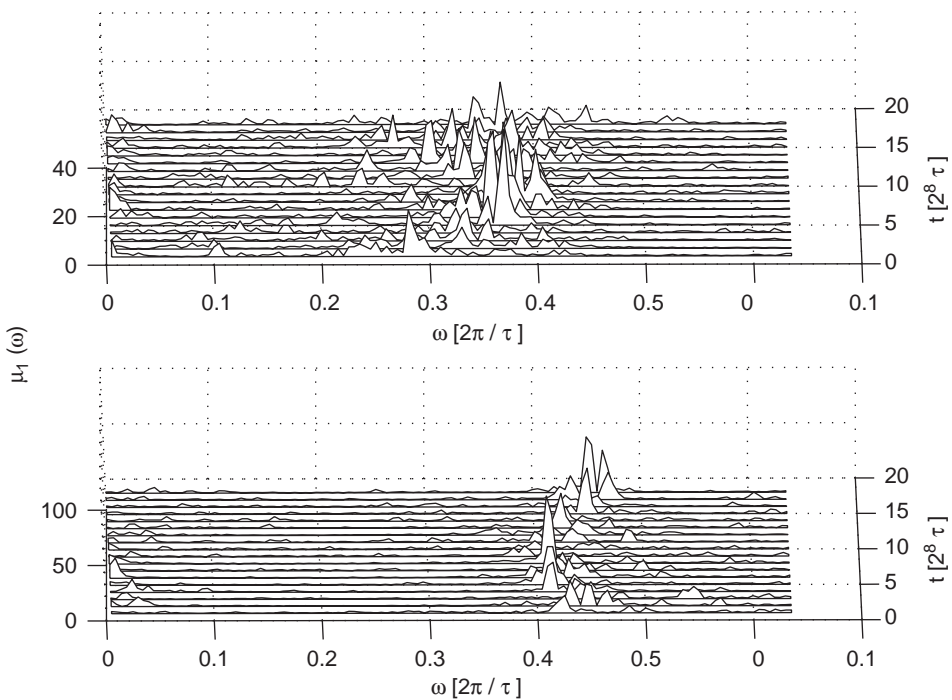

Fig. 4. The window-time behavior of the first memory function power spectra $\mu_1(\omega)$ for young and elderly people. On certain frequencies the dynamic peaks are distinctly visible in both power spectra. These peaks are connected with respiratory arrhythmia. These peaks are shifted towards higher frequencies for elderly people. It confirms the conclusion made as a result of the analysis of the previous figure.

most appreciable dynamic splashes (peaks) in the power spectra are connected with respiratory arrhythmia. All dynamic peaks are found in the particular range of frequencies. Generally in young people the range of these dynamic peaks meets $0.25\,\text{f.u.} < \omega < 0.45\,\text{f.u.}$ For elderly people this range is shifted to the right and meets $0.4\,\text{f.u.} < \omega < 0.55\,\text{f.u.}$ This implies amplification of cardiac activity at respiration with ageing.

4.2. Quantitative measure of the effects of non-Markovity in HRV

Any complex system has a great number of degrees of freedom. The high dimension of complex systems, the presence of strong nonlinear interactions and the feedback determine their behavior. This behavior can be characterized by Markov random processes. Strong external influence at accidents, crises and human diseases entails partial synchronization of natural chaotic behavior of complex systems. This synchronization results in the compelled organization of the structure of a real system and the occurrence of regular communications. The behavior of the system becomes more ordered. Such behavior is defined by the amplification of non-Markov statistical effects.

The basic idea of our method consists in defining the quantitative proportion between Markov and non-Markov effects of the studied stochastic process. As a quantitative measure of non-Markovity we suggest using the first point of the non-Markovity parameter $\varepsilon_1(\omega)$, where $\omega = 0\,\text{f.u.}$ The physical sense of this parameter consists in distinguishing Markov (processes with instant or short memory) and non-Markov (processes with long-range memory) stochastic processes. The increase of this parameter ($\varepsilon_1(0) \gg 1$) means greater Markovity of conditions of the system, the reduction of this parameter describes the processes with statistical effects of non-Markovity. The increase or decrease of the non-Markovity parameter makes it possible to judge the degree of non-Markovity in the complex system. Thus non-Markov effects are characterized by the presence of long-range correlations and the amplification of statistical displays of long-range memory. Markovian processes are characterized by the amplification of short-range correlations and the reduction of the effects of statistical memory. The quantitative measure of non-Markovity $\varepsilon_1(0) = \{\mu_0(0)/\mu_1(0)\}^{1/2}$ reveals the nature of the behavior of a system.

In Fig. 5 the frequency dependence of the first three points of the non-Markovity parameter $\varepsilon_i(\omega)$, where $i = 1, 2, 3$ in young and elderly people, is submitted. The value of a quantitative measure of the degree of non-Markovity of the young man is $\varepsilon_1(0) = 6.24$. The value of this parameter of the elderly person is $\varepsilon_1(0) = 23.16$. The ratio of the quantitative measures of non-Markovity is 3.7 times. It testifies to the increase of Markovian effects in fluctuations of an R–R interval with ageing. Markovity of heart rate variability is connected with significant fluctuations in the initial signal of the elderly person.

Further we have presented statistical results of processing for the first and second age groups. In Fig. 6 we have presented the first points of the non-Markovian parameter, averaged for the group for young and elderly people. The frequency
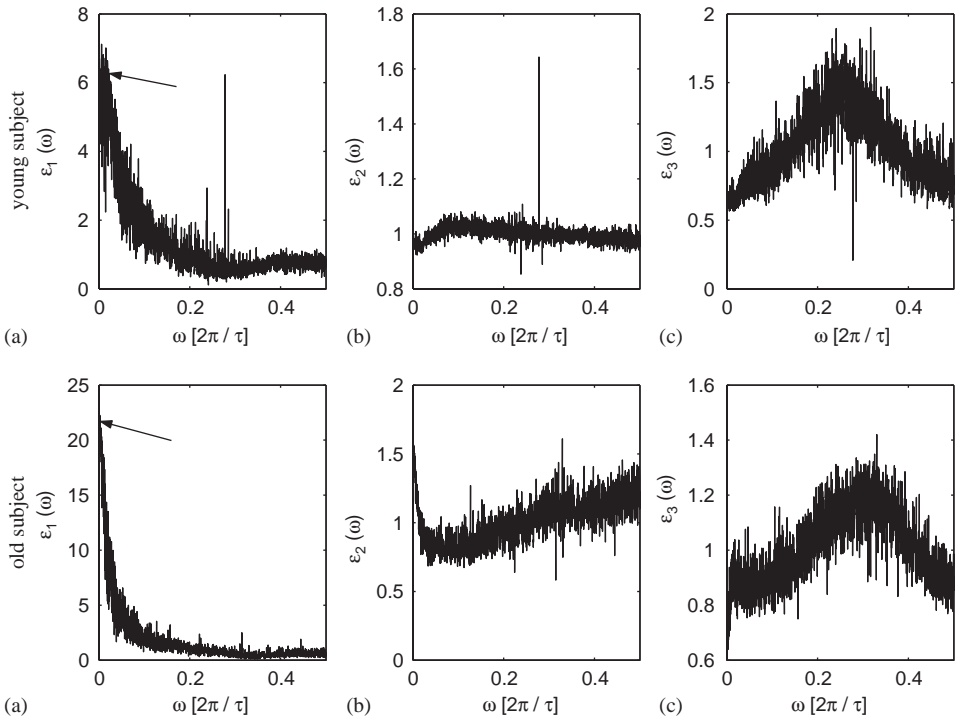
Fig. 5. The frequency dependence of first three points of the non-Markovity parameter $\varepsilon_i(\omega)$ for the young and elderly persons. The value of the first point of the non-Markovity parameter $\varepsilon_1(0)$ (a) on zero frequency is an original quantitative measure of non-Markovity of the process under study. The value of this parameter for the young man is equal to 6.24. For the elderly person the value of this parameter is equal to 23.16. The comparison of these values indicates, that the heart activity of the elderly person is characterized by the greater Markovity.

dependence of such parameters is defined as follows:

$$\varepsilon_i(\omega)_{av.val} = \frac{\sum_{j=1}^{N} \varepsilon_{i,j}(\omega)}{N}, \quad i = 1, \ldots, 3,$$

$$\varepsilon_1(\omega)_{av.val} = \frac{\sum_{j=1}^{10} \varepsilon_{1,j}(\omega)}{10}, \ldots.$$

The value of the first point of the non-Markovity parameter $\varepsilon_1(0)_{av.val}$ of young people is 6.41. The value of this parameter for elderly people is equal to 27.41. The ratio of these values is 4.2 times. It testifies to the amplification of Markov effects in the heart activity in elderly people. Therefore the number of Markov components affecting the heart activity increases with ageing.

4.3. Age-related alterations of relaxation modes

The local relaxation parameters allow to estimate the relaxation rate in the systems. The procedure of localization enables to reveal internal peculiarities of the
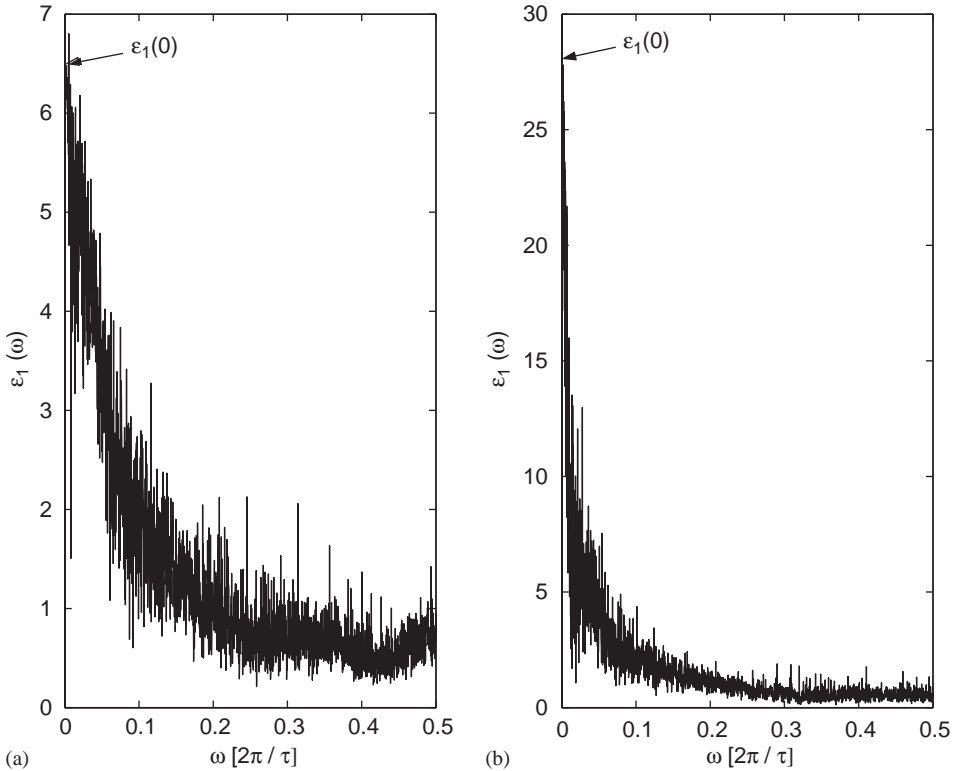
Fig. 6. The frequency dependence of the first point of non-Markovity parameter, averaged on the group of young (a) and elderly (b) people. These figures allow to define the generalized degree of Markovity and non-Markovity for the first and second age groups. The ratio of quantitative measures of the degree of non-Markovity $\delta = \varepsilon_1(0)_{old}/\varepsilon_1(0)_{young}$ for the second and first age groups constitutes 4.2 times. This implies that the variability of an R–R interval of elderly people becomes more Markovian (for the whole group). The heart activity of young people becomes more ordered and is characterized by high regularity.

dynamics of cardiac activity, latent for usual correlation analysis. The idea of the method consist in the following. From the initial time series we take a sampling N points in length for which we calculate kinetic and relaxation parameters. Then we performed "step-by-step shift to the right" operation one interval to the right and calculate kinetic and relaxation parameters. This procedure is carried out up to the end of the time series. Thus received local relaxation parameters have high sensitivity effects of alternation and non-stationarity. If there is any irregularity in the initial time series it will be instantly revealed in the time behavior of local parameters.

When using this method (as well as in the first procedure) it is necessary to define the length of the sample which allows to receive the most trustworthy information. As a result of the research of different lengths of the local sample we have calculated the optimal length which contains $2^7 = 128$ points.

In Fig. 7 we have presented the time dependence of local kinetic and relaxation parameters λ_i, where $i = 1, 2, 3$ and Λ_1, Λ_2 averaged on the group for young and elderly people. The physical sense of the first relaxation parameter λ_1 consists in defining the relaxation rate for the studied process. On average the amplitude of local parameter λ_1 for young people changes within the interval of $0.1719\tau^{-1} < \lambda_1 < 0.8522\tau^{-1}$. For elderly people this variable changes within the interval of $0.0187\tau^{-1} < \lambda_1 < 0.3580\tau^{-1}$. The ratio of root-mean-square amplitude $\langle A \rangle = \{\sum_{j=0}^{N-1} x_j^2 / N\}^{1/2}$ for young and elderly people is equal to 3.3 times. In Table 1 we present the root-mean-square amplitude, dispersion $\sigma^2 = (1/N) \sum_{j=0}^{N-1} \delta x_j^2$ and a root-mean-square deviation $\sigma = \{(1/N) \sum_{j=0}^{N-1} (x_j - \langle x \rangle)^2\}^{1/2}$ for local relaxation
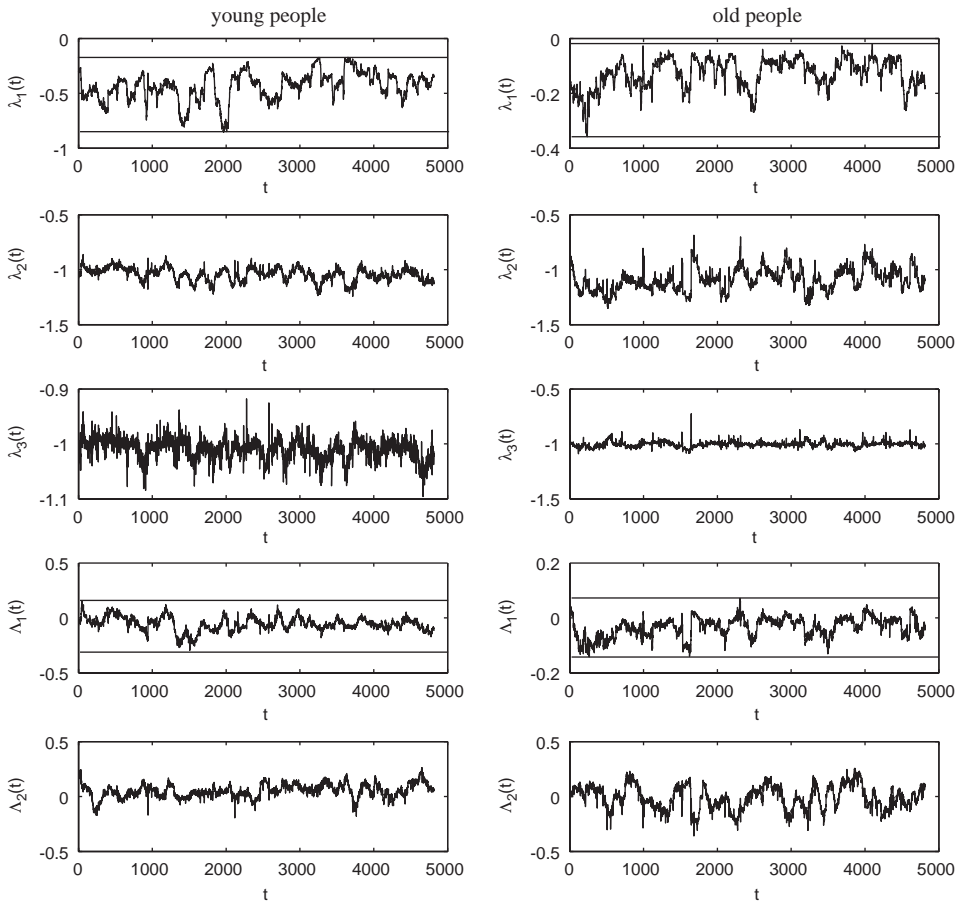

Fig. 7. The time dependencies of local kinetic and relaxation parameters $\lambda_1, \lambda_2, \lambda_3$ and Λ_1, Λ_2, averaged on the whole group for young and elderly people. The physical sense of the first relaxation parameter λ_1 consists in defining the relaxation rate. The ratio of root-mean-square amplitude of this parameter to the first and second age groups is equal to 3.3 times. It indicates to higher relaxation rate of cardiac activity for the young people.

parameters. The comparison of these characteristics indicates reduction of the relaxation rate with ageing (the increase of the relaxation time). For example, the difference of the amplitudes of relaxation parameters Λ_1 constitutes 1.7 times.

Thus, using different approaches in the research of the time series of an R–R interval we have arrived at the general conclusion. The work of a heart becomes more Markov (the effects of statistical memory disappear) with ageing and the speed of relaxation of cardiac activity is reduced.

5. Conclusion

The achieved results allow to come to the following conclusions. The procedure of localization makes it possible to calculate quantitative characteristics describing the speed of relaxation of cardiac activity. We have revealed essential distinctions in relaxation processes for different age groups on the basis of the comparative analysis of quantitative characteristics of variability of an R–R interval. The processes occurring in the heart of a young person, have a greater relaxation rate. Hence, at the appearance of any destructions in cardiac activity, faster restoration of its usual normal mode can be observed. The relaxation rate of cardiac activity decreases in elderly people. Heart activity comes back to its normal rhythm slower in this case.

The use of the first point of the non-Markovity parameter $\varepsilon_1(\omega)$ allows to estimate quantitatively Markovian and non-Markovian effects of heart rate variability (HRV). The work of a heart of an older person is characterized by greater Markovity due to the influence of a greater number of components, that reduce the effects of long-range memory (deterioration of an organism, ageing and physiological changes of a heart and other life-support systems, etc.). The comparison of values of the parameter $\varepsilon_1(\omega)$ for young and elderly people (their ratio is equal to 4.2 in case of $\omega = 0$), indicates a high degree of Markovity of HRV of elderly people. The HRV of young people is characterized by greater non-Markovity, that indicates the smaller number of its Markov components. Thus, the number of Markov components of cardiac activity increases with age.

These conclusions are interconnected and supplement each other. The increase of the number of Markov components, affecting cardiac activity, results in the increase of the relaxation time of a system. The system needs greater time for restoration to the normal operating mode. It is caused by the decrease of long-range correlations and reduction of the effects of statistical memory with ageing. On the contrary, the increase of the relaxation rate of a system testifies to the increase of the number of regular components. For example, the effects of statistical memory and long-range correlations are amplified the dynamics of HRV. A higher relaxation rate is characteristic of normal heart activity.

The procedure of the window-time behavior allows to find out additional age features of cardiac activity of a person. The frequency of cardiac reductions at breath increases with age. It shows the age-related displacement of dynamic bursts (connected with respiratory arrhythmia) in the area of higher frequencies.

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