Вісник Тернопільського національного технічного університету
https://doi.org/10.33108/visnyk_tntu
Scientific Journal of the Ternopil National Technical University
2020, № 1 (97) https://doi.org/10.33108/visnyk_tntu2020.01
ISSN 2522-4433. Web: ***visnyk.tntu.edu.ua***

UDC 519.246

METHOD OF VECTOR RHYTHMCARDIOSIGNAL AUTOMATIC GENERATION IN COMPUTER-BASED SYSTEMS OF HEART RHYTHM ANALYSIS

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Summary. *The method of automatic formation of rhythm cardiogram with increased resolution by means of already-registered electrocardiogram processing has been substantiated and used in the paper for the first time. This method enables the process of heart rhythm analysis based on rhythmcardiogram with the increased resolution be fully automated in the automatic computer-based systems of functional diagnostics of human heart condition and it is more informative in comparison with the conventional methods of heart rhythm analysis based on the classic cardiointervalogram. The methods of statistical processing of cardiointervalogram have been implemented on the basis of the mathematical model in the form of a conditional cyclic random process which is the most complete and adequate description of the model within the stochastic approach. The formation of rhythmcardiogram with the increased resolution is carried out in three stages. On the first stage the phases of the same type are supposed to be detected corresponding to the limits of zones in all heart cycles of the registered cardiogram. On the second stage the phases of the same type within the limits of the determined zones which correspond to the waves' extreme are supposed to be detected. On the third stage the differences between the determined time moments are calculated that correspond to the detected phases of the same type in all the neighboring cycles of the electrocardiosignal. The conventional segmentation methods were used in the paper to determine the limits of the segments namely, the method, which is based on the Brodsky-Darhovsky statistics and the method based on difference function of the first order. The structure of the method of rhythmcardiogram with increased resolution formation has been described in the article. Moreover, the analysis of the obtained results of relative errors of rhythmcardiogram with the increased resolution has been performed by the applied segmentation methods.*

Key words*: modeling, heart rhythm analysis, rhythm cardiogram, electrocardiosignal, segmentation methods.*

https://doi.org/10.33108/visnyk_tntu2020.01.122 *Received 10.04.2020*

Problem statement. Modeling and computer-aided analysis of heart rhythm is very important not only for the heart and vascular structures condition diagnostics but for the assessment of adaptive capabilities of a human body in general as well, as the heart rhythm represents the degree of conformity and synergy of human body functioning as an integral system [1, 2]. Nowadays, there are many stationary and portable computer diagnostic systems of human heart rhythm analysis. Most of them are based on rhythmcardiosignal stochastic mathematical models use and methods of its statistical analysis (in time and spectral domains) by its single implementation (tracing), namely rhythmcardiogram which is the sorted sum of values of heart cycles durations, for example in work [3]. The heart cycles durations are usually defined as R-R intervals durations in registered implementation of the electrocardiosignal called electrocardiogram.

Rhythmcardiosignal-based modeling and analysis of heart rhythm does not allow detecting subtle, more detailed features of heart rhythm as rhythmcardiogram describes only temporal variations of heart cycles durations but not all time intervals between the

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electrocardiosignal values per cycle for all its phases. Therefore, it is impossible to describe the heart rhythm completely. In the papers [4, 5], a new approach to the heart rhythm analysis based on the rhythmcardiogram with increased resolution has been substantiated aimed at more adequate and informative description (representation) of the heart rhythm. The rhythmcardiogram with increased resolution is the ordered sum of time intervals values between the electrocardiosignal one-phase values among which R-R intervals occur. So, a classic rhythmcardiogram is inserted into a rhythmcardiogram with increased resolution and this is the argument to increase the level of informativeness in the heart rhythm analysis in modern computer systems of functional diagnostics of human heart condition based on the rhythmcardiogram with increased resolution.

There was shown in the papers [4, 5] that the rhythmcardiogram with increased resolution can be quite reasonably considered as a discrete random rhythm function of a conditional cyclic random process which is a mathematical model of electrocardiosignal. Besides, the above-mentioned papers have substantiated the use of vector of random values as a mathematical model of the rhythmcardiogram with increased resolution. The vector dimension equals to the number of different phases in the electrocardiosignal for which certain time intervals were determined which are the values of rhythmcardiogram with increased resolution.

One of the most important stages of heart rhythm analysis by a rhythmcardiogram with increased resolution is the process of this rhythmcardiogram formation from the electrocardiogram as the resolution of the initial cyclic signal of heart electric activity. In the previous papers [4, 5], the formation of a rhythmcardiogram with increased resolution was not automatic but has to be performed by experts-cardiologists who have done the procedure manually and it has resulted in low level of the whole process of heart rhythm analysis automation.

The purpose of the article under discussion is to substantiate and apply the method of rhythmcardiogram with increased resolution electrocardiosignal automatic formation from the registered signal to increase the automation level of heart rhythm analysis on the basis of rhythmcardiogram with increased resolution in the computer systems of human heart condition functional diagnostics.

Known research analysis. There are numerous methods for a classic rhythmcardiogram automatic formation from the electrocardiogram. All these methods are based on the sequential implementation of three main stages: 1) electrocardiogram segmentation into cycles that is mainly implemented by detection of QRS-complexes and R-waves maxima of the electrocardiogram; 2) finding the differences between the time intervals which correspond to the detected R-waves maxima for all pairs of the electrocardiogram neighboring cycles; 3) building the rhythmcardiogram as a discrete function which is given on the set of all time intervals where R-waves maxima were detected and the values of the function in certain time intervals were equal to the difference between the time intervals which correspond to the detected R-waves maxima for two neighboring cycles of the electrocardiogram.

Four main classes of RR-intervals have been distinguished among the conventional methods (algorithms): a) the algorithms making analysis of electrocardiosignals in time domain; b) the algorithms based on frequency-temporal, including nonlinear, transformations of electrocardiosignals; c) the algorithms that use the neural networks; d) combined, hybrid algorithms that employs the combinations of algorithms from different classes [6–21].

In the algorithms of the first class, the nonlinear transformations are widely used that involve the electrocardiosignal integrating in a sliding window. Due to the above-mentioned approach R-wave is detected by the electrocardiosignal level threshold which is fixed in advance or detected adaptively. Different frequency and time transformations are used in the second-class algorithms, namely, Fourier, Karhunen-Loeve, wavelet transformations. Neural networks are used in the third-class algorithms for data processing aimed at electrocardiosignals segments classification during their morphological analysis. Neural networks are also used for adaptive matched filtration in the problems of QRS-complexes identification that enables adapting to the electrocardiosignal non-stationary behavior. The last class of algorithms uses different combinations of methods that allows eliminating the drawbacks of certain classes of algorithms and it is mostly the synthesis of algorithms of classes (b) and (c) or (a) and (c). The main disadvantage of the last class of methods and algorithms is considerable calculation requirements to the resources of their implementation.

Paper purpose. The aim of the paper is to develop the method of electrocardiosignal processing which allows increasing the level of heart rhythm analysis automation based on the electrocardiosignal-based rhythmcardiogram with increased resolution in computer systems of human heart condition functional diagnostics. The developed method not only enables the heart rhythm analysis be automated on the basis of the rhythmcardiogram with increased resolution but it is also more informative comparing to the conventional methods of heart rhythm analysis based on the classic cardiointervalogram.

Problem statement. According to the above-mentioned problem and literature analysis the main task of the article under consideration is to develop a method of rhythmcardiogram automatic formation with increased resolution from the already-registered electrocardiogram that enables complete automation of the heart rhythm analysis based on the processing of the rhythmcardiogram with increased resolution and makes possible the increase of informative value level of heart rhythm analysis in modern computer systems of functional diagnostics of human heart condition.

Research methods. There was developed the method of rhythmcardiogram automatic formation with increased resolution from the already-registered electrocardiosignal implementation, namely from the electrocardiogram. There are many well-known mathematical models of electrocardiosignals though their most complete and adequate description according to the stochastic approach can be performed on the basis of a cyclic random process and a conditional cyclic random process [22–25]. Conditional cyclic random process involves a cyclic random process as its particular case. According to the papers [4, 5, 25], the process $\{\xi(\omega,\omega',t), \omega\in\mathbf{\Omega}, \omega'\in\mathbf{\Omega}', t\in\mathbf{R}\}$ is called a conditional cyclic random process, which is defined on the Cartesian product of two stochastically independent stochastic spaces with elementary event sets $\mathbf{\Omega}$ and $\mathbf{\Omega}'$ and on the real numbers set $\mathbf{R}$, when the following requirements are satisfied: 1) there is such a random function $T(\omega',t,n), \omega'\in\mathbf{\Omega}', t\in\mathbf{R}, n\in\mathbf{Z}$, where for each ω', the corresponding ω'–implementation $T_{\omega'}(t,n)$ of this function satisfies the rhythm function requirements; 2) for each ω' from $\mathbf{\Omega}'$ finite-dimensional vectors ($\xi_{\omega'}(\omega,t_1)$, $\xi_{\omega'}(\omega,t_2)$,..., $\xi_{\omega'}(\omega,t_k)$) and ($\xi_{\omega'}(\omega,t_1+T_{\omega'}(t_1,n))$, $\xi_{\omega'}(\omega,t_2+T_{\omega'}(t_2,n)))$,..., $\xi_{\omega'}(\omega,t_k+T_{\omega'}(t_k,n))$), $n\in\mathbf{Z}$, where $\{t_1, t_2,...,t_k\}$ is the process separability set $\xi_{\omega'}(\omega,t), \omega'\in\mathbf{\Omega}', \omega\in\mathbf{\Omega}, t\in\mathbf{R}$, for all integers $k\in\mathbf{N}$ are stochastically equivalent in a broad sense; 3) for any different $\omega_1'\in\mathbf{\Omega}'$ and $\omega_2'\in\mathbf{\Omega}'$ stochastic processes $\xi_{\omega_1'}(\omega,t)$ and $\xi_{\omega_2'}(\omega,t)$ are isomorphic with respect to the order and values of cyclic random processes.

Implementation (ω'-implementation) of random function $T(\omega',t,n)$ is deterministic function $T_{\omega'}(t,n)$, that satisfy the rhythm function conditions, namely: 1) a group of conditions: a) $T_{\omega'}(t,n)>0$, if $n>0$ ($T_{\omega'}(t,1)<\infty$); b) $T_{\omega'}(t,n)=0$, if $n=0$; c) $T_{\omega'}(t,n)<0$, if $n<0$, $t\in\mathbf{R}$; for any $t_1\in\mathbf{R}$ and $t_2\in\mathbf{R}$, for which $t_1<t_2$, for the function $T_{\omega'}(t,n)$ strict inequality $T_{\omega'}(t_1,n)+t_1<T_{\omega'}(t_2,n)+t_2, \forall n\in\mathbf{Z}$ holds true; 3) function $T_{\omega'}(t,n)$ is the smallest by module ($|T_{\omega'}(t,n)|\le|T_{\omega'}^{\gamma}(t,n)|$) among all such functions $\{T_{\omega'}^{\gamma}(t,n),\gamma\in\mathbf{\Gamma}\}$, which satisfy the above-stated requirements 1 and 2.

The mathematical model of a rhythmcardiosignal with increased resolution, according to the papers [4, 5], is a discrete stochastic process $\left\{T(\omega',t_{ml},n),\omega'\in\mathbf{\Omega}',t_{ml}\in\mathbf{R},m\in\mathbf{Z},l=\overline{1,L},L\ge2,n\in\mathbf{Z}\right\}$, that is inserted into the random rhythm function $T(\omega',t,n),\omega'\in\mathbf{\Omega}',t\in\mathbf{R},n\in\mathbf{Z}$ of conditional cyclic random process $\{\xi(\omega,\omega',t),\omega\in\mathbf{\Omega},\omega'\in\mathbf{\Omega}',t\in\mathbf{R}\}$. Thus, the mathematical model of a rhythmcardiogram, is ω'-implementation $\left\{T_{\omega'}(t_{ml},n),t_{ml}\in\mathbf{R},m\in\mathbf{Z},l=\overline{1,L},L\ge2,n\in\mathbf{Z}\right\}$ of discrete random process $\left\{T(\omega',t_{ml},n),\omega'\in\mathbf{\Omega}',t_{ml}\in\mathbf{R},m\in\mathbf{Z},l=\overline{1,L},L\ge2,n\in\mathbf{Z}\right\}$. So, the domain of rhythmcardiogram is a discrete set of real numbers $\mathbf{D}=\left\{t_{ml},m\in\mathbf{Z},l=\overline{1,L},L\ge2\right\}$, where index m is the number of electrocardiosignal cycle, and index l is the number of electrocardiosignal count within its m th cycle. Number of counts L per electrocardiosignal cycle determines the rhythmcardiogram resolution and specifies the number of phases per electrocardiosignal cycle which can be derived by segmentation and detection methods while solving the task of rhythmcardiogram automatic formation from the already-registered electrocardiogram.

As in case of classic rhythmcardiogram the process of automatic formation of the rhythmcardiogram with increased resolution consists of three main stages: 1) determine the phases of the same type corresponding the boundaries of the zones in all heart cycles of the already-registered electrocardiogram; 2) detecting the phases of the same type within the specified zones corresponding to maxima or minima of P-, Q-, R-, S- and T-waves, respectively; 3) finding the differences between the time intervals corresponding to the detected phases of the same type (zones boundaries and waves maxima or minima) in all neighboring cycles of the electrocardiosignal and building the rhythmcardiogram with increased resolution as a discrete function specified on the set of all time intervals which correspond to the defined phases of the heart cycle. In this case, the values of the function in certain time intervals equal to the difference between the time intervals corresponding the detected phases of the same type for two neighboring cycles of the electrocardiosignal (see Figure 1).

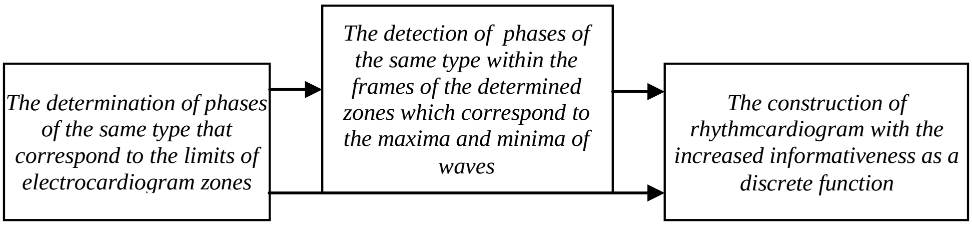

Figure 1. The scheme of formation method of rhythmcardiogram with increased resolution

The first and second stages of the method of rhythmcardiogram with increased resolution formation are the most difficult computationally and contribute greatly to its automatic formation error. Phases of the same type detected in all heart cycles of the already-registered electrocardiogram is provided by its segmentation into cycles and smaller segment-zones (for example, *P*, *T*, *U* waves), and also, if necessary, determination of their extreme (maximum and minimal) values. There are many well-known methods and algorithms of electrocardiosignals segmentation. For instance, temporal, frequency-temporal algorithms based on wave transformations and neural networks based algorithms are widely used classes of electrocardiosignals segmentation algorithms [26–33]. Temporal algorithms involve the analysis of amplitude characteristics of an electrocardiosignal and have low computational complexity of their implementation. Their disadvantages include considerable sensitivity to the presence of technical and biological artifacts of the studied electrocardiosignal. Frequency-temporal algorithms based on wave transformation are characterized by high noise tolerance though they are rather ambiguous concerning the choice of the best shape and length of the window in which the studied electrocardiosignal is being analyzed. The use of neural networks based algorithms allows solving the problems of recognizing and classification of the defined diagnostic segments during the electrocardiosignal processing. The efficiency of such class of algorithms operation mostly depends on the previously performed neural network training and also on the efficient methods of previous processing as they are sensitive to the presence of any noise in the electrocardiosignal.

In the current study, to solve a problem of electrocardiosignal segmentation there was used the method developed in the papers [34, 35] based on the Brodsky-Darhovsky statistics which is sensitive to any changes in mathematical expectation of the electrocardiosignal. The considered method makes the already specified segments of the electrocardiosignal received by the Brodsky-Darhovsky statistics more precise to increase the accurateness of electrocardiosignal segmentation into cycles and smaller zones within the boundaries of each cycle. Figure 2 shows the structural-functional scheme of the method of electrocardiosignal segmentation applied in the paper that is based on the Brodsky-Darhovsky statistics and rhythmcardiogram with increased resolution formation as a discrete rhythm function of conditioned cyclic random process.

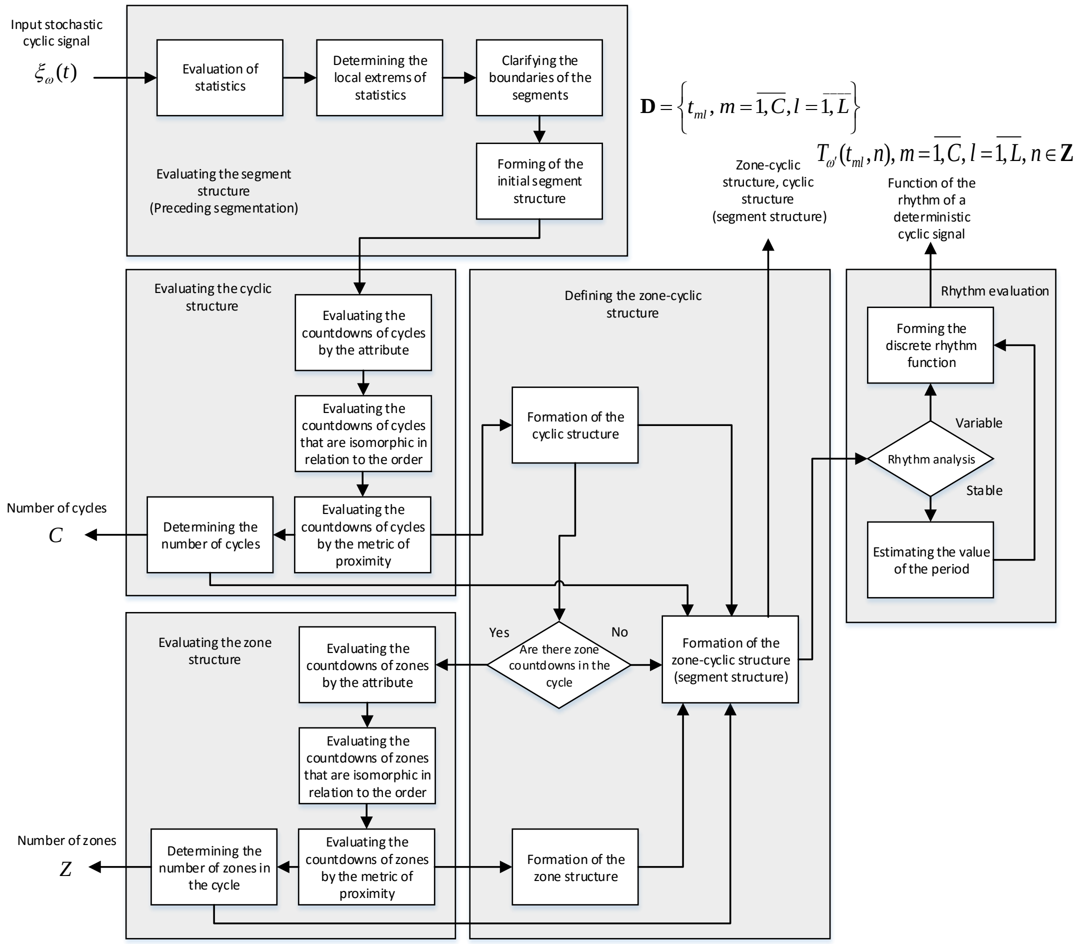

Figure 2. The scheme of electorocardiogram segmentation method based on the Brodsky-Darhovsky statistics and rhythmcardiogram with the increased resolution formation

Results of the research. Let's consider an example of automatic formation of a rhythmcardiogram with increased resolution based on the above described method. Figure 3 shows a curve of several cycles of the studied electrocardiogram. Figure 4 shows the result of its segmentation based on the applied method.

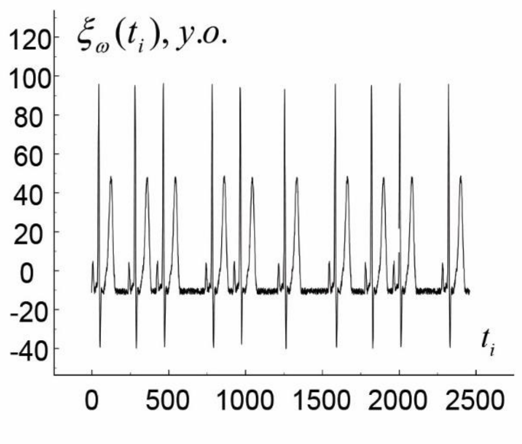

Figure 3. The results of several cycles processing of the studied electrocardiogram

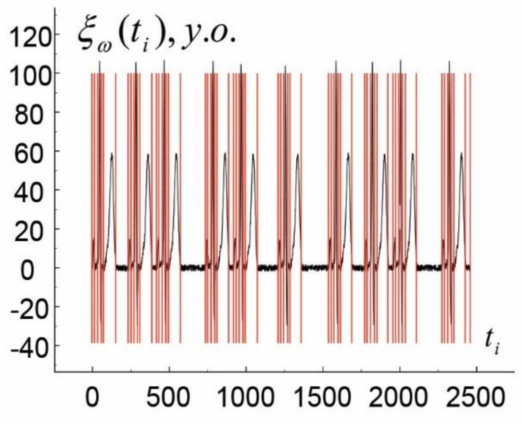

Figure 4. The results of the studied electrocardiogram segmentation using the method based on the Brodsky–Darhovsky statistics

To compare the obtained results on the basis of Brodsky–Darhovsky statistics there was performed the electrocardiogram segmentation and the rhythmcardiogram with increased resolution was formed using the known method of segmentation based on the difference function of the first order. Figure 5 shows a plot of rhythmcardiogram formed by the method based on the Brodsky–Darhovsky statistics. Figure 6 presents a plot of rhythmcardiogram formed by the method using the difference function of the first order.

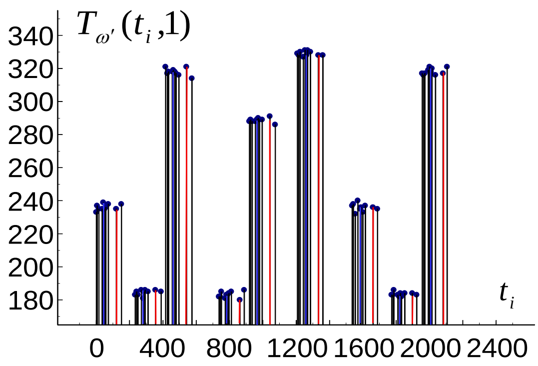

Figure 5. The results of rhythmcardiogram with the increased resolution processing that is formed by the segmentation method, and detection of extreme values of electrocardiogram zones, which is based on the Brodsky–Darhovsky statistics

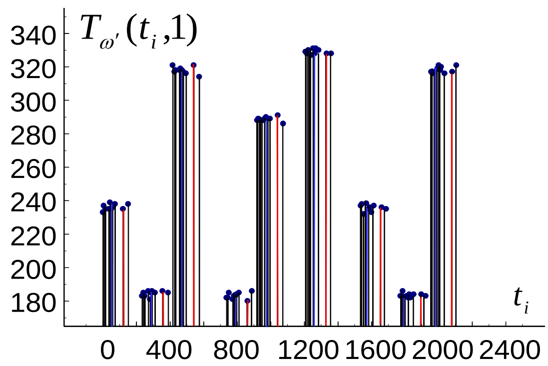

Figure 6. The results of electrocardiogram processing with increased resolution that is based on the segmentation method, and detection of extreme values of electrocardiogram zones based on the difference function of the first order

Figure 7 shows the plots of relative errors of rhythmcardiogram with increased resolution countdowns formation that correspond to R–R cardiogram intervals which were obtained on the basis of the segmentation method and extreme values of electrocardiogram zones that were detected based on the Brodsky–Darhovsky statistics (bullet points on the plot) and on the basis of method using the difference function of the first order (triangles on the plot). Figure 7 describes the plots of relative errors of rhythmcardiogram with increased resolution countdowns formation that correspond to T-T intervals and that were obtained on the basis of the segmentation method and extreme values of electrocardiogram zones detecting based on the Brodsky–Darhovsky statistics (bullet points on the plot) and on the basis of method using the difference function of the first order (triangles on the plot).

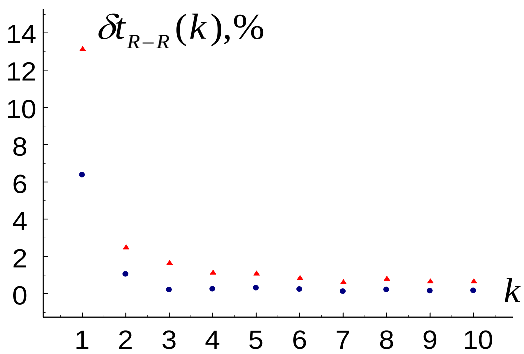

Figure 7. The plots of relative errors of rhythmcardiogram with increased resolution countdowns formation that correspond to R–R cardiogram intervals

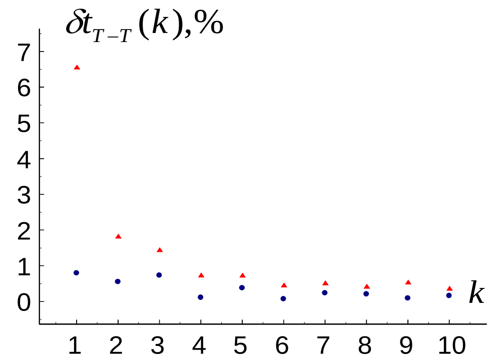

Figure 8. The plots of relative errors of rhythmcardiogram with increased resolution countdowns formations that correspond to T–T cardiogram intervals

After the performed analysis of the relative errors plots of rhythmcardiogram with increased resolution countdowns formation presented on figures 7 and 8, is can be seen that the method of automatic formation of rhythmcardiogram with increased resolution based on the Brodsky–Darhovsky statistics is more accurate than the same method based on the difference function of the first order.

Conclusions. There was developed the method of rhythmcardiogram automatic formation with increased resolution from the already registered electrocardiogram that makes the process of heart rhythm analysis fully automated in computer systems of human heart condition functional diagnostics. Moreover, the studied method is more informative comparing to the conventional methods of heart rhythm analysis which are based on classic cardiointervalogram. The method of rhythmcardiogram with increased resolution automatic formation based on the segmentation method and extreme values of electrocardiogram zones that were detected based on the Brodsky–Darhovsky statistics has proved to be more accurate than the same method based on the difference function of the first order.

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УДК 519.246

МЕТОД АВТОМАТИЧНОГО ФОРМУВАННЯ ВЕКТОРНОГО РИТМОКАРДІОСИГНАЛУ В КОМП'ЮТЕРИЗОВАНИХ СИСТЕМАХ АНАЛІЗУ СЕРЦЕВОГО РИТМУ

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Резюме. *Вперше обгрунтовано та застосовано метод автоматичного формування ритмокардіограми з підвищеною роздільною здатністю шляхом опрацювання попередньо зареєстрованої електрокардіограми. Даний метод дає змогу повністю автоматизувати процес аналізу серцевого ритму на базі ритмокардіограми з підвищеною роздільною здатністю в автоматизованих комп'ютерних системах функціональної діагностики стану серця людини та є більш інформативним у порівнянні з відомими методами аналізу серцевого ритму на основі класичної кардіоінтервалограми. Методи статистичного опрацювання кардіоінтервалограми реалізовані на базі математичної моделі у вигляді умовного циклічного випадкового процесу, що є найбільш повним та адекватним її описом у рамках стохастичного підходу. Формування ритмокардіограми з підвищеною роздільною здатністю проводиться у три етапи: перший передбачає визначення однотипних фаз, які відповідають межам зон у всіх серцевих циклах зареєстрованої електрокардіограми; другий – детектування однотипних фаз у межах визначених зон, які відповідають екстремумам зубців, відповідно; третій етап передбачає визначення різниць між визначеними моментами часу, які відповідають детектованим однотипним фазам в усіх сусідніх циклах електрокардіосигналу. Для визначення меж сегментів у роботі використано відомі методи сегментування, зокрема метод, в основі якого покладено статистику Бродського-Дарховського та метод, в основі якого використовується різницева функція першого порядку. Описано структури методу формування ритмокардіограми з підвищеною роздільною здатністю, а також проведено аналіз отриманих результатів відносних похибок формування ритмокардіограми з підвищеною роздільною здатністю на основі використаних методів сегментації.*

Ключові слова: *моделювання, аналіз серцевого ритму, ритмокардіограма, електрокардіосигнал, методи сегментації.*

https://doi.org/10.33108/visnyk_tntu2020.01.122 *Отримано 10.06.2020*