Improving the reliability of cardiological diagnostics of arrhythmias using stochastic parameters of spectral dynamics of rhythmograms

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***Abstract*—The article presents the results of a theoretical analysis of the parameters of a two-dimensional autocorrelation function and it`s filtering in time, the results of dynamic modeling of arrhythmia identification procedures using training rhythmograms. The possibility of intellectualization of identification procedures using the statistical procedure of Wald's sequential analysis has been proved. Results of parametric identification of cardiac conditions by changes in the characteristics of correlation-spectral non-stationarity of rhythmograms in a sliding observation window**

***Keywords*—rhythmogram, atrial fibrillation, stochastic parameters, autocoherence model, non-stationarity**

I. ANNOTATION

The use of measuring information about the heart rate by rhythmograms is traditionally considered informationally limited. This is due to the impossibility of restoring all the parametric properties of the cardiocycle, which are traditionally use to identify cardiac disorders. However, if we consider the rhythmogram as a discretized spectrally random process, then the use of the dynamic properties of such non-stationarity in time and frequency representations allows one to obtain quantitative parametric information about non-stationarity both in the frequency range and in the localized observation time interval. Frequency non-stationarity is traditionally characterize by the autocoherence function and has been study quite well. The non-stationarity of the spectrum at local time intervals is only now beginning to receive its probabilistic statistical justification. For this purpose, the most informative are mixed cumulants of the second and higher orders, which characterize the stochastic relationship between two (leading and lagging) wavelet spectra in a localized observation window. The time shift between such spectra should be frequency weighted and at least discretely adjustable. Then, unlike the autocoherence function, the spectral non-stationarity function in time will be equivalent to the two-dimensional autocorrelation function of the rhythmogram with a fixed time shift.

The article presents the results of a theoretical analysis of the parameters of a two-dimensional autocorrelation function and it`s filtering in time, the results of dynamic modeling of arrhythmia identification procedures using training rhythmograms. This makes it possible to increase the resolution of the proposed method for the identification of arrhythmias, with the possibility of controlling the resolution and reliability of identification according to predetermined risks of errors of the first and second kind.

The article presents the results of parametric identification of cardiac conditions by changes in the characteristics of correlation-spectral non-stationarity of rhythmograms in a sliding observation window. Such characteristics reflect both the frequency and time uncertainties of the amplitude spectrum of the rhythmogram. They base on the calculation of the correlation coefficients between the lagging and leading two-dimensional spectra of the rhythmogram in a sliding window. The positioning of the spectra in such a window is frequency-weighted, providing the same multiplicity of displacements with respect to the period of each harmonic.

The sequential identification procedure reduces the decision-making time by more than five times as compared to the deterministic procedure. The resolution of the procedures increases by the same factor. Additional advantages of the developed procedure for identifying arrhythmias include the possibility of assessing the time point characterizing the change in the model of the non-stationarity of the object under study (change in its state “norm-arrhythmia” or “arrhythmia-norm”).

II. PROBLEM

Today, diseases of the cardiovascular system are leading all over the world. Therefore, the healthcare sector is trying to find ways to reduce this situation by early diagnosis of abnormalities in the cardiovascular system, when the disease is only of an initial nature, and therefore can be easily eliminated.

One of the simplest diagnostic methods is the study of heart rate variability, which analyzes the heart rate and its change over time. Chaotic deviations in the duration of the time intervals between heart contractions, violation of heart rate variability, are called arrhythmia. The danger of arrhythmias lies in mild symptoms, which subsequently lead to severe complications.

Atrial fibrillation occurs when the electrical conduction of the atria is disturbed, accompanied by uncoordinated electrical activity of the atria with a subsequent deterioration in their contractile function, and leading to an increase in the risk of stroke, heart failure, heart attacks and other diseases [1, 2]. The danger of this arrhythmia is the possibility of an asymptomatic course of the disease with pronounced deterioration at the stage of a chronic state. The prevalence of the disease is about 1% of the world's population under the age of 60 years and more than 6% after the age of 60 years [3, 4].

Detection of atrial fibrillation is possible only with prolonged screening and adequate analysis of cardiac activity. On the market of electronic devices for detecting atrial fibrillation, there are both medical devices and systems, and various gadgets [5-7]. Their common feature is the mandatory presence of a mathematical algorithm for identifying deviations in heart rate variability. However, medical devices use sophisticated but more accurate methods for detecting arrhythmias compared to gadgets [8]. However, on the other hand, medical devices have a shorter lifespan than gadgets, and identification is carried out upon completion of the examination process.

Thus, to date, an urgent task has been formed on the application of highly informative methods of automatic detection in real time, based on spectral changes in dynamic objects, which include biological objects. This will allow the use of procedures for the intellectualization of algorithms for making diagnostic decisions in real time, based on objectively adequate probabilistic models of frequency and time non-stationarity of rhythmograms.

III. LITERATURE ANALYSIS

Arrhythmia detection is carried out using various algorithms, which are based on the analysis of electrocardiogram (ECG) constituent sections by detecting irregularity of RR intervals (the duration between two adjacent R waves) and in the change in the magnitude of the P wave with the possibility of replacing the T wave as a result of abnormally fast atrial activity [9].

Determination of atrial fibrillation based on the change in the value of the P wave is a more reliable method. However, it requires more laborious calculation processes and high quality ECG [10-13]. Therefore, it is carried out exclusively on the already registered ECG signals in order to exclude extraneous noises , as well as by external electric fields that surround the patient in everyday life.

The use of methods for determining atrial fibrillation based on the irregularity of the rhythms of heart contractions has an indirect approach, as the assessment is carried out indirectly by changing the RR intervals (rhythmogram) [14-17]. However, this approach is simpler in calculations and requires significantly less computational resources. In turn, this allows such methods to be used in portable devices for real-time arrhythmia detection, which can prevent unwanted consequences from cardiac abnormalities.

Recent studies show that the onset of atrial fibrillation occurs after disturbances in the rhythm of cardiac activity caused by other types of arrhythmias [18]. On the one hand, such violations can lead to false definitions of atrial fibrillation, but on the other hand, this can allow predicting its onset in the near future. To detect arrhythmias based on rhythmograms, various methods of statistical signal processing are used, which can be divided into several groups.

The first group includes methods of direct analysis of rhythmograms based on the coefficients of variation. The essence of the methods is to compare the coefficients of variation of the RR intervals and ΔRR (the difference between adjacent RR intervals) with the standard coefficients of variation corresponding to the state of atrial fibrillation [15]. At values that are equal to atrial fibrillation in a certain set interval, a decision is made on the presence of arrhythmia. However, the sensitivity and specificity of this method is not great. The best performance is possessed by the method based on comparing the histograms of the density of the RR and ΔRR intervals with the standard histogram of the density using the Kolmogorov-Smirnov test [15, 16]. If the difference in the values of the comparison results of the RR and ΔRR test is insignificant, then a decision is made about the presence of atrial fibrillation.

The second group includes methods based on the analysis of the entropy of time series RR intervals. A method based on the analysis of the entropy of a sample, which is used to assess the complexity of physiological signals of time series in the diagnosis of disease states. The change in the entropy value indicates the similarity of RR intervals in the time series (high value - low similarity, low value - high similarity) [17, 18]. In the method based on Shannon's entropy, the estimation of the RR values of intervals in the time series is performed with the white noise signal, which has the highest entropy value due to the maximum uncertainty in predicting the signal [17, 19].

The third group includes methods for analyzing the root mean square values of successive differences. Because atrial fibrillation exhibits higher variability than normal sinus rhythm, the root mean square of the successive differences are more significant than normal. To exclude subjective differences, the value of RR intervals is normalized by dividing by the standard deviation of the RR time series [17].

The development of statistical methods for signal processing, as well as the use of existing methods for the analysis of new processes, creates opportunities for methods of processing rhythmograms. Among these are the method based on the use of integrated moving average autoregression models, which analyzes the order of the models that change at different rhythms of cardiac activity [18]. A more complex method of multifractal analysis of the wavelet leader of heart rate variability, the essence of which is to use discrete wavelet analysis and fractal analysis to assess the variability index and Hurst exponent, respectively. The use of multifractal analysis based on wavelets allows one to analyze the temporal fluctuation of the local regularity of RR intervals in episodes of atrial fibrillation and other rhythms [20].

IV. INTEGRAL AUTOCOHERENCE MODEL

Any processes associated with the work of the heart and their characteristics are fundamentally non-stationary, since their probabilistic parameters (mean value, variance, spectral density, etc.) are no invariant in time.

There are known mathematical models of autocoherence functions that allow detecting random modulation of harmonics of periodically non-stationary signals [18-20] by their correlation at fixed frequencies ω. Such models have a significant drawback associated with the obligatory fixation of these frequencies for the same observation time instant, ignoring the time intervals at which such modulation may appear or disappear. In fact, the known models of autocoherence functions do not take into account the dynamics of changes in non-stationarity. To take into account such dynamics, it is necessary to localize a section of the rhythmogram *x(t)* with possible non-stationarity and consider two spectra of this section separated by a time interval. This interval can be achieved by differentiating the process *x(t)* at a localized site. Then the harmonics of the spectrum of the derivative *x´(t)* will lag behind the corresponding harmonics of the original process *x(t)* by exactly half the period for each harmonic. If for some of the harmonics, in the interval of its shift, the effect of factorial influence on the stationarity model appears, then such an effect can be detected based on the assessment of the correlation between the corresponding harmonics of the compared spectra.

Since we are talking about localized spectral analysis, it is advisable to use wavelet transforms (continuous or discrete) to obtain two-dimensional spectra. In such spectra, frequency parameters are characterized by a scale *a*, and temporal ones – by a shift *b*.

For discretized continuous wavelet transform, the two-dimensional spectrum will be represented by a set *N* of wavelet coefficients $W\left(a_j, b_i\right)$, $j=\overline{1,h}$, $i=\overline{1,m}$, de *h* – the number of scales, *m* – the number of shifts [21-23].

Let us introduce the notation for the wavelet coefficients V_{ji} of the main process *x(t)* and the wavelet coefficients U_{ji} of the differentiated process *x´(t)*.

$$\begin{gathered} m\sum_{j=1}^{h}(\overline{V}_j-\overline{V})(\overline{U}_j-\overline{U})+\sum_{j=1}^{h}\sum_{i=1}^{m}(V_{ji}-\overline{V}_j)(U_{ji}-\overline{U}_j)= \\ h\sum_{i=1}^{m}(\overline{V}_i-\overline{V})(\overline{U}_i-\overline{U})+\sum_{j=1}^{h}\sum_{i=1}^{m}(V_{ji}-\overline{V}_i)(U_{ji}-\overline{U}_i) \end{gathered} ,(1)$$

where, $\overline{V}_j$, $\overline{V}_i$ – are the group averages of the wavelet coefficients V_{ji} in scale and shift, respectively; $\overline{U}_j$, $\overline{U}_i$ – the group averages of the wavelet coefficients U_{ji} for the scale and shift, respectively.

Let us introduce the notation $Q_1^{(a)}$, $Q_2^{(b)}$ for the first and, respectively, the second terms of the right-hand side of expression (1). Similarly, for the terms on the right-hand side of the same expression, we use the notation $Q_1^{(b)}$, $Q_2^{(a)}$. Then expression (1) can be represented as follows:

$$Q_1^{(a)}+Q_2^{(b)}=Q_1^{(b)}+Q_2^{(a)}. \tag{2}$$

We will take into account that the wavelet coefficients V_{ji} and U_{ji} are equivalent to the amplitudes of the spectral components and are related by the relation

$$U_{ji}=\omega_j\cdot V_{ji}\cdot\left(t_i-\frac{\pi}{2\cdot\omega_j}\right). \tag{3}$$

Let us introduce a notation for the phase shift in expressions (3)

$$\tau_j=\frac{\pi}{2\cdot\omega_j}. \tag{4}$$

Taking into account the two-dimensionality of the wavelet spectrum in frequency (specified by the scale *a*) and in time (specified by the shift *b*), we introduce into the model for random estimates the wavelet coefficients V_{ji} and U_{ji} the terms of the parametric model of analysis of variance.

1. Frequency model (to scale)

$$V_{ji}^{(a)}=\overline{V}+\delta_j^{(a)}+z_{ji}^{(b)}, \tag{4}$$

where $\delta_j^{(a)}$ – the functional variable of the wavelet coefficients V_{ji} along the scale axis, due to the influence of the factor of spectral nonstationarity (at a fixed observation time); $z_{ji}^{(b)}$ – random (residual) changes in the wavelet coefficients of the spectrum with time (at a fixed scale).

2. Time model (by shift)

$$V_{ji}^{(b)}=\overline{V}+\delta_j^{(b)}+z_{ji}^{(a)}, \tag{6}$$

where $\delta_i^{(b)}$ – the functional variable of the wavelet coefficients V_{ji} along the shear axis, due to the influence of the factor of spectral non-stationarity (at a fixed scale); $z_{ji}^{(a)}$ – random (residual) changes in the wavelet coefficients of the spectrum in frequency (with a fixed observation time).

In models (5) and (6), the last terms characterize the uncertainty of each of the models and are their random residuals.

We will take into account that the mathematical expectation of the product of the centered wavelet coefficients is a second-order mixed central moment (cumulant)

$$\varkappa_{11}=\mathrm{E}\left\{V_{ji}\cdot U_{ji}\right\}. \tag{7}$$

Taking into account expressions (2), this cumulant can be represented in the form of two terms, separately for the frequency (5) and time (6) models.

For the frequency model, expression (7) will take the form:

$$\varkappa_{11}=\left(\frac{h-1}{N-1}\right)\cdot Q_1^{(a)}+\left(\frac{N-h}{N-1}\right)\cdot Q_2^{(b)}. \tag{8}$$

For a temporary model, expression (7) will take the form

$$\varkappa_{11}=\left(\frac{m-1}{N-1}\right)\cdot Q_1^{(b)}+\left(\frac{N-m}{N-1}\right)\cdot Q_2^{(a)} \tag{9}$$

Expressions (8) and (9) allow us to consider the first terms as some informative parameters $\xi^{(a)}$ and $\eta^{(b)}$ are analogs of the autocoherence function, filtered, respectively, in time and frequency, taking into account phase shifts (expression (4)) $j=\overline{1,h}$. The filtered noise (residual) components are presented in the form of informative parameters $\xi^{(b)}$ and $\eta^{(a)}$ corresponding to the second term of expressions (8) and (9).

Passing to the limits (at *N*→∞), we obtain simplified expressions for informative parameters:

$$\xi^{(a)}=\lim_{N\to\infty}\left(\frac{h-1}{N-1}\right)\cdot Q_1^{(a)}=m^{-1}E\left\{\overline{V_j}\left(\bar{t}\right)\cdot\overline{V_j}\left(\bar{t}-\tau_j\right)\right\}, \tag{10}$$

$$\xi^{(b)} = \lim_{N\to\infty}\left(\frac{N-h}{N-1}\right)\cdot Q_2^{(b)} = E\left\{\Delta V_i\left(\bar{\tau}\right)\cdot\Delta V_i\left(t_i-\bar{\tau}\right)\right\}, \quad (11)$$

$$\eta^{(b)} = \lim_{N\to\infty}\left(\frac{m-1}{N-1}\right)\cdot Q_1^{(b)} = h^{-1}E\left\{\overline{V_i}\left(\bar{t}\right)\cdot\overline{V_i}\left(t_i-\bar{\tau}\right)\right\}, \quad (12)$$

$$\eta^{(a)} = \lim_{N\to\infty}\left(\frac{N-m}{N-1}\right)\cdot Q_2^{(a)} = E\left\{\Delta V_j\left(\bar{t}\right)\cdot\Delta V_j\left(\bar{t}-\tau_j\right)\right\}. \quad (13)$$

The right parts of expressions (10-13) are estimated data of informative parameters that carry information about the time-frequency or time-frequency form of stochasticity of the basic wavelet rhythmogram in a fixed observation window. At the same time, the non-stationarities in terms of mathematical expectation and in terms of variance are separately identified. Moving such a window to the right converts the estimate into time-discretized random processes (time series). Such series are characterized by both amplitude and frequency random changes. The latter can be assessed by means, for example, correlation intervals, or the intensity of zero crossing.

Expressions (10) and (12) indicate that the time shifts (τ_j or $\bar{\tau}$) between the lagging spectrum *U* and the leading one *V* (for the same observation window) provide an opportunity to test the hypothesis according to which there are no changes in the wavelet coefficients of the main signal spectrum *x(t)* in the shift intervals τ. This means that the correlation between any harmonic of the spectrum *V* and the corresponding harmonic of the spectrum *U* is a sign-changing function of time, and the number of periods of such a change is 2. The extreme values of the correlation itself oscillate between +1 and -1, with an average value of 0. If in intervals shift τ changes in any spectral components of the differentiated process *x´(t)*, then the extreme values of the informative parameters $\xi^{(a)}$ and $\eta^{(b)}$ decrease (modulo). In this case, the characteristics of the informative parameters $\xi^{(a)}$ and $\eta^{(b)}$ will change, such as the variance and the intensity of their zero crossing. It becomes possible to control the changes in non-stationarity models in the observation window for any of the specified characteristics.

Expressions (11) and (13), in contrast to (10) and (12), estimate correlations between random deviations of spectral harmonics *U* and *V* from their mathematical expectations, respectively, in the time and frequency domains. The values of the informative parameters $\xi^{(a)}$ and $\eta^{(b)}$ carry information related to the residual variances of the spectra used *U* and *V*, make it possible to estimate the residual autocoherence of the base spectrum in time and frequency.

It should be noted that the new informative parameters $\xi^{(a)}$, $\xi^{(b)}$ and $\eta^{(b)}$, $\eta^{(a)}$ expand the capabilities of the traditional autocoherence function by localizing the moments of time that separate the variants of probabilistic models of spectral changes in the process *x(t)*.

As an initial process, the study used rhythmograms from the MIT-BIH database, which contain areas of atrial fibrillation development. In fig. 1 rhythmogram MIT-BIH-07879 (RR) and also changes in informative parameters indicating the time sites with established atrial fibrillation (*Afib*). The rhythmogram and informative parameters are presented in the form of time series corresponding to 10 hours of signal registration.

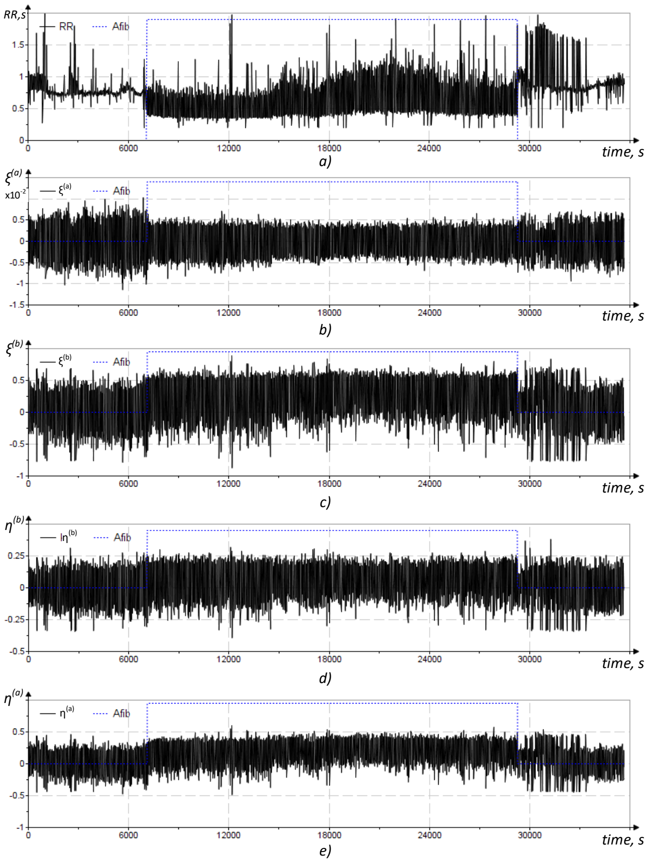

Fig. 1. a) rhythmogram with atrial fibrillation; b) temporary parameter changes $\xi^{(a)}$; c) temporary parameter changes $\xi^{(b)}$; d) temporary parameter changes $\eta^{(b)}$; e) temporary parameter changes $\eta^{(a)}$

As can be seen from Fig. 1, the dependence of informative parameters on time has a random character, non-stationary in variance. This is indicated by an abrupt change in the nature of the dispersion at the time interval corresponding to the presence of fibrillation.

Studies have shown that changes in informative parameters in time, are also non-stationary in the intensity of zero crossings. Figure 2 shows the estimates of the values of the intensity of the intersections obtained in the sequential observation window. An estimate of this frequency is the intensity of crossing a common zero and, as can be seen from Fig. 2, its informativeness, in comparison with the informative parameters of Fig. 1, is higher (especially for $\xi^{(a)}$).

Moreover, the frequency interpretation of the informative parameters in Fig. 1 allows the use of tests based on mathematical models of Wald's sequential statistical analysis to identify areas of the rhythmogram with different cardiac states [24-26]. The advantages of such tests are: a) the ability to manage the levels of identification risks not only of the first, but also of the second kind; b) the possibility of intellectualizing the testing procedure, by using a sliding observation window of random width. The window is dynamic, and its width is automatically determined by the procedure itself, based on the specified risks.

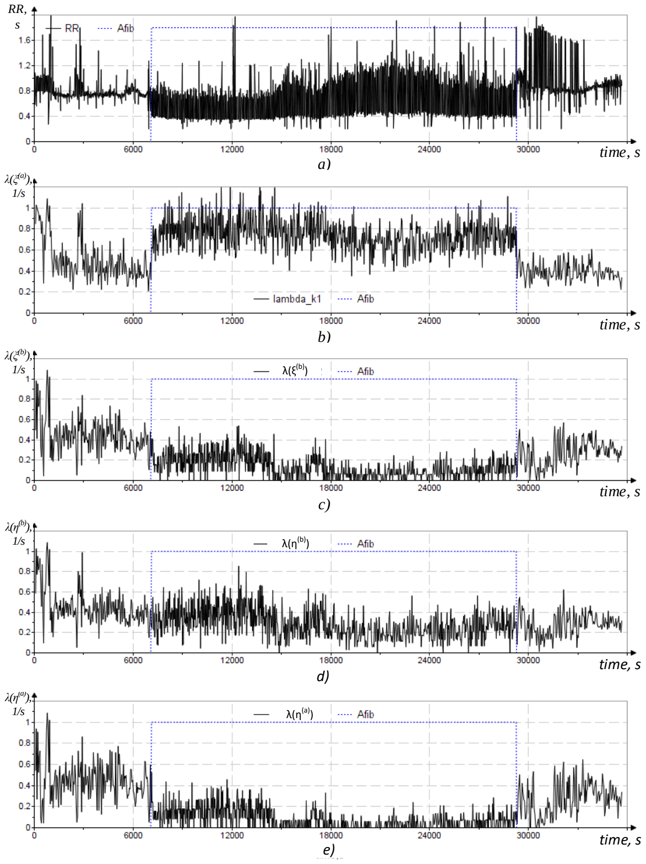

Fig. 2. Time series of intersection intensities "0" in consecutive observation windows for (window width 50 heart rate)

The disadvantage of the sequential analysis test is the need for preliminary training of the procedure, based on an a priori given probabilistic model of the distribution of time intervals between adjacent zero-crossing times. Moreover, such training should be carried out for areas of the rhythmogram with verified cardiac conditions (norm and pathology).

V. SEQUENTIAL ANALYSIS TEST

For testing, we use the time series in Fig. 1. The sequence of zero crossings in such series will be considered a flow of random events that satisfies the following requirements: a) ordinary – events in the stream are single; b) independence – the probability of the occurrence of the next event does not depend on the probability of the occurrence of the previous event; c) stationarity – the flow rate for a fixed cardiac state is constant.

If the listed requirements for the event flow are met, then such a flow in the general case is a Poisson flow with intensity λ_j (j – cardio state number). To estimate this intensity, we will use a dynamic observation window that sequentially moves along the time axis. For a Poisson flow, the time intervals between adjacent events will have an exponential distribution with a parameter λ_j.

Naturally, the assumption about the validity of the Poisson model of the flow of zero crossings is not exact, but it allows constructing a simple mathematical model of criterion statistics with varying boundaries for its critical zone.

Using the logarithm of the maximum likelihood ratio ln(Λ) for two conditional exponential distributions with intensities λ_0 (norm) and λ_1 (pathology), and denoting as Δ the random width of the dynamic observation window, we obtain an expression for criterion testing statistics

$$\ln(\Lambda) = K \cdot \ln(\lambda_1/\lambda_0) - (\lambda_1 - \lambda_0)/\Delta . \tag{14}$$

Let us introduce the notation S for the diagnosed conditions: $S0$ – norm, $S1$ – pathology and for possible solutions γ (0,1,01) with respect to the type of state and stopping or continuing the accumulation of information (by increasing the random width of the observation window Δ)

$$\begin{cases} \gamma_0 : \ln(\Lambda) \le \ln(\beta/(1-\alpha)), \Rightarrow S \in S_0; \\ \gamma_1 : \ln(\Lambda) \ge \ln((1-\beta)/\alpha), \Rightarrow S \in S_1; \\ \gamma_{01} : \ln(\beta/(1-\alpha)) < \ln(\Lambda) < \ln((1-\beta)/\alpha), \Delta++. \end{cases} \tag{15}$$

Let us introduce the notation Δ*min* and Δ*max* for linear functions that determine the boundaries of the critical zone for Δ random width of the dynamic window. Moreover, the boundaries of such a zone are linear functions ln(Δ)

$$\begin{cases} \Delta_{\min} = \dfrac{k \cdot \ln(\lambda_1/\lambda_0)}{(\lambda_1 - \lambda_0)} - \dfrac{\ln((1-\beta)/\alpha)}{(\lambda_1 - \lambda_0)}; \\ \Delta_{\max} = \dfrac{k \cdot \ln(\lambda_1/\lambda_0)}{(\lambda_1 - \lambda_0)} + \dfrac{\ln((1-\alpha)/\beta)}{(\lambda_1 - \lambda_0)}. \end{cases} \tag{16}$$

The corresponding solutions can also be reformatted for the used observation window width Δ:

$$\begin{cases} \gamma_0 : если\ \Delta \ge \Delta_{\max}; \\ \gamma_1 : если\ \Delta \le \Delta_{\min}; \\ \gamma_{01} : если\ \Delta_{\min} < \Delta < \Delta_{\max}. \end{cases} \tag{17}$$

It should be noted that when testing with a fixed, in time, observation window, the logarithm of the likelihood ratio (14) should be compared with zero. The choice of a solution is determined by conditions.

$$\begin{cases} \gamma_0 : \text{if } \ln(\Lambda) > 0; \\ \gamma_1 : \text{if } \ln(\Lambda) \le 0. \end{cases} \tag{18}$$

In expression (14), the intensity value λ_1 is a linear function of the ratio of percentage points $\chi^2_{2\cdot k;\,\beta}$ and $\chi^2_{2\cdot k;\,1-\alpha}$ distribution with $2k$ number of degrees of freedom for given values of risks α and β.

$$\lambda_1 = \lambda_0 \cdot \frac{\chi^2_{2\cdot k;\,\beta}}{\chi^2_{2\cdot k;\,1-\alpha}} . \tag{19}$$

The width of the fixed observation window can be set both in time and λ_0.

To compare the effectiveness of the proposed dynamic testing method with the method using a fixed observation window, the rhythmogram MIT-BIH-07879 was taken. Table 1 shows the results of statistical evaluation of the risks of the first and second kind for the obtained diagnostic solutions. The parameters of the experimental design for each of the studied test models were the same ($\alpha = \beta = 0.05$). The same table gives estimates of the numerical characteristics for real values of the number of rhythms in observation windows. The average width of the fixed and dynamic windows is approximately the same (the difference does not exceed 10%).

TABLE I. RESULTS OF TESTING MODELS

Type window	Risk and reliability			Estimates of the numerical characteristics			
				Norm		Afib	
	α	β	P	Aver	RMS	Aver	RMS
Fixed	0,063	0,535	0,701	57,1	12,8	73,3	12,9
Dynamic	0,107	0,020	0,937	44,9	31,2	65,16	47,7

It follows from the table that:

– the reliability of diagnostics using a dynamic model is higher (0.937> 0.701), which indicates a higher efficiency of the testing model with a dynamic window;

– the risk of the second kind β is more than 25 times lower (0.02 << 0.535), which indicates a higher statistical power of the decision rule when using a dynamic window;

– the average width of the dynamic window is always (for any of the cardiac states) less than the fixed window, which indicates increased efficiency in making diagnostic decisions.

Table 2 shows the options for using the testing model with a dynamic window for different set diagnostic risks.

TABLE II. RESULTS OF DYNAMIC TESTING

Parameters of the experiment plan		Risk and reliability			Estimates of the numerical characteristics			
					Norm		Norm	
α	β	α^*	β^*	P	Aver	RMS	Aver	RMS
0,05	0,05	0,107	0,020	0,936	44,975	31,23	65,165	47,695
0,01	0,01	0,114	0,008	0,939	67,123	43,783	98,714	65,173
0,001	0,001	0,114	0,004	0,941	99,624	60,542	146,64	86,987
0,0001	0,0001	0,114	0,005	0,941	131,04	70,111	194,69	108,16
0,00001	0,00001	0,107	0	0,947	167,35	99,655	244,57	119,15
0,000001	0,000001	0,105	0	0,948	197,96	108,61	292,59	144,03

It follows from the table that there is always the possibility of controlling the dynamic diagnostic model in order to reduce the risk of the second kind β or the observation window.

VI. CONCLUSIONS

1. The efficiency of application of localized spectral wavelet analysis with the subsequent covariance decomposition of two-dimensional spectra is shown to obtain amplitude and frequency parameters that carry information about the types of cardiac states.

2. The information content of the frequency parameters, reflecting the change in the wavelet spectra in terms of mathematical expectation and dispersion, has been proved.

3. The possibility of increasing the reliability of atrial fibrillation diagnostics by frequency wavelet parameters has been proved by applying a procedure in which a sliding observation window has a random width.

4. The possibility of obtaining a zero value of the risk of diagnostics of the second kind by changing the parameters of the sequential procedure (assigned risks of the experiment plan) has been proved.

5. The possibility of increasing the efficiency of decision-making has been proven by minimizing the average width of the dynamic observation window.

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