

UDC 004.021

Galina Y. Shcherbakova¹, Doctor of Technical Sciences, Professor of the Information Systems Department, E-mail: Galina_onpu@ukr.net, ORCID: 0000-0003-0475-3854

Viktor N. Krylov¹, Doctor of Technical Sciences, Professor of the Applied Mathematic and Information Technology Department, E-mail: Viktor_Krylov@gmail.com, ORCID: 0000-0003-1950-4690

Olha E. Plachinda¹, Candidate of Technical Sciences, Associate Professor of the Oil and Gas and Chemical Engineering Department, E-mail: olga_plach2017@ukr.net, ORCID: 0000-0003-3382-229X

¹Odessa National Polytechnic University, Avenue Shevchenko, 1, Odessa, Ukraine, 65044

DETERMINATION OF CHARACTERISTIC POINTS OF ELECTROCARDIOGRAMS USING MULTI-START OPTIMIZATION WITH A WAVELET TRANSFORM

Abstract. The description of the main steps of the method for determination of the coordinates of the extremums of non-stationary periodic signals is given. This method is based on multi-start optimization using the wavelet transform. The main steps of the base form of multi-start optimization method with using the wavelet transform are given. The results of investigation of noise stability and error for the search of extremums of asymmetric and multi-modal test functions for such method are given. The main steps of extremum search by such method in new method for determination of the coordinates of the extremum of non-stationary periodic signals are implemented. This method is implemented for automated electrocardiograms (ECG) diagnostic systems in telemedicine. This method allowed us to determine characteristic fragments coordinates for electrocardiogram. The procedure for estimation of the characteristic fragments coordinates and intervals between them is based on this multi-start optimization method with using the wavelet transform. The main steps of this procedure are described. The error in estimating the duration of the intervals between ECG characteristic fragments was estimated and the noise immunity of such estimation with increasing the noise level was evaluated. The relative error in estimation of the intervals duration between characteristic fragments was less than 4% in the case of the signal-to-noise ratio in amplitude up to 10. These results allow recommending the developed method for implementation in information technologies for automated decision support systems, including telemedicine, in condition of increasing noise level in ECG signals. For further research, it is planned to develop a methodology for estimation the remaining parameters of characteristic fragments and complexes in ECG, reducing the edge effects during the estimation of the extremums coordinates.

Keywords: multistart optimization; wavelet transform; electrocardiogram; arrhythmia; diagnostics

Introduction. An important task of modern information technologies in various applied areas of medical diagnostics is the need to create methods for analyzing non-stationary periodic signals.

Such signals are characteristic of diagnostic systems based on the analysis of electrocardiograms (ECG) in such an applied field as telemedicine. In such systems at the stage of registering signals and transmitting them over communication lines, the signal is distorted by noise. In systems that analyze signals only in the frequency or time domain, when the spectra of the useful signal and noise overlap, the reliability of the diagnostic solutions may decrease.

Therefore, an important modern trend is the analysis of such signals using wavelet transform. This approach allows us to localize the characteristic fragments of the ECG signal by using the important property of the wavelet transform – to change sign when passing through the signal extremums. This last property allows us to determine the coordinates of the characteristic fragments and/or to determine the coordinates of the extremums of the signal.

This data can be used to determine the classification vector and diagnostics in the decision support system.

Characteristic fragments will be called the periodically repeating sets of local extrema (minima and maxima) of the ECG signal that are traditionally used for diagnostics in this applied area (Fig. 1). Characteristic points (CP) will be called the extremums of the curvature functions of the ECG signal. Analysis of the coordinates of the chemotherapy is one of the important components in obtaining a diagnostic solution in the decision support system.

When determining the classification vector based on wavelet ECG processing, several solutions with conflicting features have been proposed. For example, a number of authors proposed that the usage of the result of ECG wavelet processing as a classification vector directly leads to a decrease in the diagnostic speed. The use of intervals for this, in which characteristic regions of the ECG signal are located, requires large data sets processing, which also reduces performance, and for some tasks, for example, the detection of arrhythmias, can lead to a decrease in the reliability of diagnostics.

At the present stage, several solutions with conflicting features have been proposed for determining

the classification vector based on ECG wavelet processing. For example, a number of authors suggest using ECG wavelet processing result directly as a classification vector. This approach leads to a decrease in the speed of diagnosis. Using the intervals in which characteristic regions of the ECG signal are located as a classification vector requires the processing of large data sets. It also reduces performance, and in some tasks, for example, when detecting arrhythmias, it can lead to a decrease in the reliability of diagnosis.

In a number of works, to improve performance, the classification vector is reduced. The characteristic points of the ECG signal are determined by gradient search and fixed threshold processing. But this approach is characterized by low noise immunity and sensitivity to local extremes. In the case of the diagnosis of cardiac arrhythmias, it can lead to a decrease in the reliability of the diagnosis.

To analyze noisy and multimodal functions, the authors developed a multi-start optimization method using wavelet transform. This method in the basic setting is characterized by high noise immunity and low sensitivity to local extremums and the starting point of the search.

Literature review. Analysis of existing systems and methods in the application field

Methods for the analysis of non-stationary periodic signals are sufficiently developed and are widely used in various applied fields of medical diagnostics. For example, in telemedicine systems [1] when analyzing local features of a pulse signal [2] and when analyzing electrocardiograms (ECG) [3-11] (Table 1) that method are necessary.

Important features of the software of such software systems are the ability to recognize characteristic ECG fragments and characteristic signal points, measuring and analyzing changes in the intervals between them.

ECG signals are usually distorted by noise. These noises occur during the registration of signals and during data transmission over communication lines, which is typical for such systems. Therefore, the traditional study of such signals based on the analysis of only time or frequency characteristics is a set of separately tunable complex algorithms [12]. Such approaches under conditions of overlapping spectra [13] of the useful ECG signal and noise can lead to a decrease in the reliability of diagnostic solutions [5].

New methods are actively being developed, that are aimed at identifying new features of the ECG signals characteristics of various groups of diseases [23-24]. For example, an approach aimed at processing the ECG signal in the phase space [23],

when reconstructing the signals, uses the averaging of consecutive ECG cycles in the time domain. This approach requires the analysis of large data sets, but can lead to a distortion of the values of the parameters of the diagnostic signs of the ECG [24].

Table 1. Existing software systems for analysis and interpretation of ECG signals

| Name | Manufacturer | Key features |
|---|------------------------|---|
| ECG interpretation software C [6] | Schiller (Switzerland) | Analysis of heart rhythm changes (more than 100 ECG interpretation options) |
| Signal-Averaged ECG Software (SAECG) [7] | Schiller (Switzerland) | Analysis of heart rhythm changes |
| Heart Rate Variability (HRV) Software [8] | Schiller (Switzerland) | Analysis of heart rhythm changes |
| Marquette 12SL [9] | GE Healthcare (USA) | Arrhythmia Detection, ST Segment Analysis |
| Cardiosoft [10] | GE Healthcare (USA) | ST segment analysis, automatic measurement of ECG intervals, arrhythmia analysis, noise filtering |
| FP-804 [11] | Fukuda (Japan) | Analysis of changes in PR, RR and QRS intervals |
| Telecard [25;26] | TREDEX (Ukraine) | Analysis of heart rhythm changes |

The use of wavelet transform (WT) with the ability to analyze local features of the ECG signal in the time domain allows us to overcome these limitations to a large extent [3; 12-15]. Often, with the support of a diagnostic solution, the results of processing with WT are used directly as a classification vector [15]. This approach leads to a decrease in performance due to an increase in the dimension of the classification vector. For example, determining the intervals in which the characteristic areas of the ECG signal and the wavelet functions (WF) scale are located. At the same time, it is assumed that the range of WF scales in a particular person during the day is unchanged [16-17]. This approach is justified in the analysis of large sets of signals, for example, when using the Holter monitor, when the number of ECG cycles can exceed 100,000 [16-17]. Performance can be improved with small sets of analyzed signals, but that can lead to incorrect diagnostic decisions.

To ensure high performance [5], the dimension of the classification vector is reduced by determining the coordinates of the characteristic points of ECG fragments (Fig. 1).

They are determined by evaluating the extremum of the signals according to the value of derivatives and threshold processing of their period values [13]. The procedure for determining derivatives is characterized by low noise immunity [18-19], and the assessment of the period with a fixed threshold with high heart rate variability, for example, with arrhythmia [16-17], can lead to a decrease in the reliability of diagnostic solutions.

To search for the extremum of noisy polymodal functions, a multi-start optimization method using WT (MOWT) was developed, the noise immunity of which was proved by the authors [18-19].

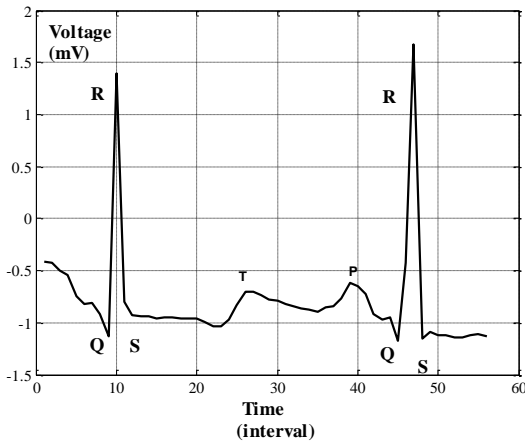


Fig. 1. A standard ECG waveform with PQRST complex

The purpose of the article. In this work, by basing on the method for searching the extremums of non-stationary periodic signals with using a number of stages of the multi-start optimization method with wavelet transform, the method of search of ECG characteristic points coordinates and of the intervals is developed. This approach will automate the receipt of the classification vector, increase the noise immunity and reduce the sensitivity to local extremums during classification with the data obtained during diagnosis.

Main part. Method for finding the coordinates of the extremum of periodic signals

In this work as a result of studies of noise immunity, convergence rate and error, it was concluded that to estimate the direction of the search for the extremum coordinates in (2), it is necessary to use symmetric and non-stationary wavelet functions – Haar's wavelet [18].

According to the basic iterative scheme of the multi-start method with wavelet transform, the coordinate of the extremum is estimated as

$$c[n] = c[n-1] - \gamma[n]WT_k(Q(x[n], c[n-1])), \quad (1)$$

where: $\gamma[n]$ – iteration step; n – number of iterations; k – number of a start; WT_k determines the direction of movement to the extremum and is calculated according to:

$$WT_k(Q(x[n], c[n-1])) = \{G_{1k}, G_{2k}, \dots, G_{Nk}\}, \quad (2)$$

where: G_{jk} determines the direction of movement to the extremum and is calculated according to:

$$G_{jk} = \frac{1}{S_k} \sum_{\substack{i=-\frac{s_k}{2} \\ i \neq 0}}^{\frac{s_k}{2}} Q(x[n], c_j + ia) \cdot \Psi_k(i), \quad (3)$$

s_k – length of the WF carrier; a – step of discretization of the WF; $\Psi_k(i)$ – WF at the k start (Table 2); $j = 1, \dots, N$ – the dimension of the parameter vector.

$$WT_k(Q(x[n], c[n-1])) = \{G_{1k}, G_{2k}, \dots, G_{Nk}\}, \quad (4)$$

determines the direction of motion to the extremum, where

$$G_{jk} = \frac{1}{S_k} \sum_{\substack{i=-\frac{s_k}{2} \\ i \neq 0}}^{\frac{s_k}{2}} Q(x[n], c_j + ia) \cdot \Psi_k(i), \quad (5)$$

In (5) s_k (an even number) is the length of the carrier WF at the k -th start, a is the WF sampling step, $\Psi_k(i)$ is the WF on k -th start (Table 2, Fig. 2), $j = 1, \dots, N$ is the dimension of the parameter vector.

So, for example, at 1 start, this is the Haar wavelet function, which is defined as

$$\Psi_1(i) = \begin{cases} 1, if & i = 1, \dots, \frac{S_1}{2} \\ -1, if & i = -1, \dots, -\frac{S_1}{2} \end{cases}$$

At subsequent starts, except the last one, and – at the next stages – unsteady WFs from the indicated class (Fig. 2), which are obtained according to the scheme given in Table. 2. The main stages of the

basic method of multi-start optimization with wavelet transform are given below.

Table 2. WF parameters for MOWT methods

| Number of start | k | 2 | 3 | 4 | 5 | 6 | 7 | |
|------------------|-------------|------------------------------------|----|---|---|---|--|--|
| WF scale | α_k | 1 | 2 | 3 | 4 | 5 | - | |
| Carrier length | s_k | 20 | 10 | 6 | 4 | 4 | 2 | |
| Type of function | $\Psi_k(i)$ | $\frac{1}{\alpha_k \cdot ((i+1))}$ | | | | | $\begin{cases} 1, \text{ if } i=1 \\ -1, \text{ if } i=-1 \end{cases}$ | |

Method MOWT with the initial data: δ_1 – error of searching the optimum in the start (determined at the priori studies of the goal function); δ_2 – error of searching the optimum for the application problem; k_{\max} – the maximum number of starts, is implemented by the following steps.

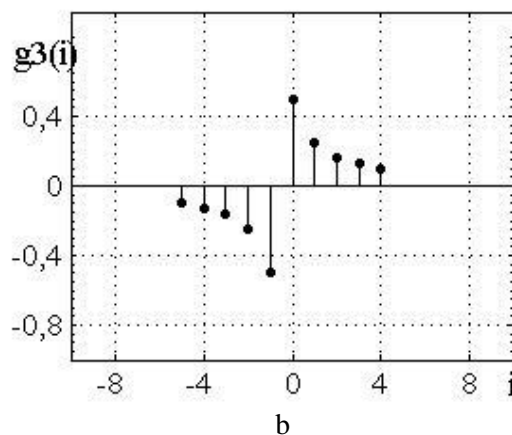
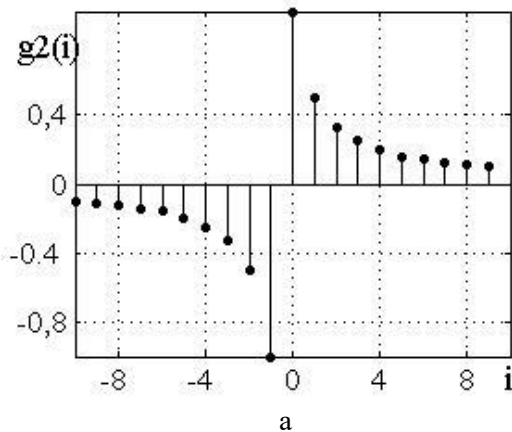


Fig. 2. The impulse response and for WF $\Psi_2(i)$ (a); $\Psi_3(i)$ (b) to evaluate the search direction

Step 1. There are defined: $c[0]$ – the initial ap-

proximation to the optimum coordinate, $\gamma[1]$ – iteration step, a form of WT and WF, a – a sampling step of WF, s_1 – the carrier length for WF in the first start, number of the start $k=1$, number of the iteration $n=1$.

Step 2. The search direction is estimated on a base of (4, 5) at a point closer to the optimum coordinate for the start k . Under $k=1$ a weighted sum with the WF $\Psi_1(i)$ at the point $c[0]$ ($n=1$) is used to evaluate the direction of the search. The carrier length L_{\max} of the wavelet function $\Psi_1(i)$ is determined by analysis of the objective function. The integrated nature of this WF can reduce the sensitivity towards local extremums and select a segment of the objective function, which includes (with a high probability) the global optimum, and (often) with a high error of determine its coordinates.

Step 3. The search is running for the optimum of $Q(x, c)$ according (3) and $k \leq k_{\max}$, otherwise search is stopping.

Step 4. If the coordinate $c[n]$ – found on iteration n – differs from the optimum position $c[n-1]$ not more than the value of the error δ_1 , the search ends at the current start, otherwise the increment $n = n + 1$ is making with a following transfer to step 2.

Step 5. If $k > 1$ and the optimum coordinate – found at the k -th start – differs from the result of the optimum at the start $k - 1$ not more than δ_2 then a process is stopping; otherwise ($k \leq k_{\max}$), the number of start increases as $k = k + 1$ to evaluate WF for selecting the search direction (for $1 < k < k_{\max}$ – WF $\Psi_k(i)$ (see Table 2), with $k = k_{\max}$ the search direction is evaluated by the discrete differentiation ($k=7$ in Table 1)) and a process is switched to a step 2.

Experimental studies of this optimization method are carried out, and the rate of convergence, the value of the accuracy and robustness are evaluated.

To estimate the error of the extremum determining by the method MOWT with both WF $\Psi_1(i)$ and WF $\Psi_3(i)$ the asymmetric test function $f_1(x) = x^2 * e^{xm}$ is synthesized with $x \in (-500; 500)$, where $m = 0 \dots 0,005$ is the adjustment coefficient of the asymmetry. Authors

established that relative error of defining the optimum $f_1(x)$ with WF $\Psi_1(i)$, under the sampling step $a=50$ and the carrier length of the WF $s_1 = 10$, does not depend on the initial search point. Moreover it's directly proportional to the asymmetry factor, and it equals 0.34 % for the maximum studied coefficient $m=0.005$ (Fig. 3a curve 1), and the absolute error equals 0.3. For evaluation with $\Psi_3(i)$ these errors are equal 0.1 % (see Fig. 3, a curve 2), and 0.08, respectively.

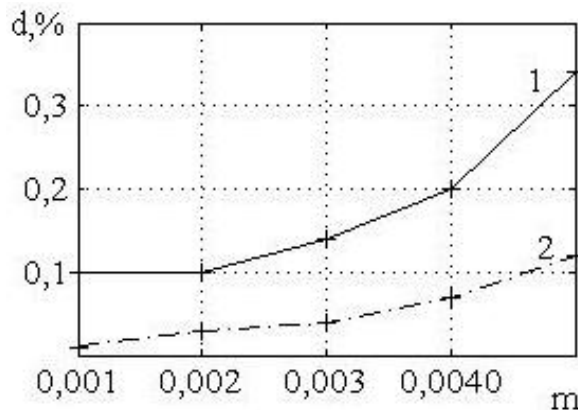


Fig. 3. Relative error (d) of asymmetry coefficient (m) at determining the extremum: a curve 1 – with WF ($\Psi_1(i)$); a curve 2 – with $\Psi_3(i)$

The velocity of convergence for the method MOWD was compared with the gradient descent method using the test function “Rosenbrock valley” $f_2(x) = 100(x_2 - x_1^2) + (1 - x_1)^2$. This function for $x \in (-2, 048; 2, 048)$ has a global minimum $f_2(x) = 0$ at the $x_1 = 1, x_2 = 1$. Sampling step WF $a=0.0005$ and the carrier length $s_k = 10$ were adopted. Thus, the method MOWT enabled to reach the extremum up to 1.7 times faster (for the number of iterations) compared with the gradient descent method.

The sensitivity of the method MOWT towards the local extrema at the search starting point was studied. For this purpose we used the Shvefel's function (with the false global minimum)

$$f_3(x) = 418,9829 + (-x * \sin \sqrt{x}),$$

where $x \in (-500; 500)$, the global minimum $f_3(x) = 0$ at $x=420,9829$.

The starting point in this case was selected randomly and the gradient descent method searched the local optimum as the closest one to the starting point. As the result the method MOWT enabled to reach the global minimum with accuracy $\delta \leq 10^{-2}$ in 123 cases out of 150. Meantime the global minimum was not found by this method when the values x for the start point were selected out of the interval $x \in (-420; 470)$.

In the first step the noise immunity was investigated using de Jong 1 function $f_4(x) = x^2$ for $x \in (-205; 205)$ supplemented with a noise. The noise has the normal distribution with zero mean and standard deviation (SD) of 0 up to 40000, a maximum value of the function was $f_4(x) = 42000$. As a result it was established (for the signal/noise ratio in amplitude lower than 1.05) the MOWT method enabled to reach a domain of the global minimum with an error $\delta \leq 10^{-2}$.

Thus, experimental studies have shown the developed method MOWT has the following advantages:

- sensitivity to local extremum and the starting point of the search is reduced;
- minimum relative error is reduced for evaluating the search direction with WF $\Psi_k(i)$ and $k > 1$;
- optimum is reached in 1.7 times faster (for the number of iterations) in a comparison with the gradient descent method (for “valley” functions);
- noise immunity of this method is estimated.

When the relation signal/noise by amplitude is larger than 1.05, the area of a global minimum is reached. The most noise-resistant is the assessment by convolution with WF $\Psi_1(i)$.

Received results allow us recommend the developed method for a wide range of practically important optimization problems in case of the asymmetric goal functions with the high level of a noise.

Method for determining the coordinates of the extrema of unsteady signals

The determination of the coordinates of the extremum is carried out on the basis of the first stage of the basic MOWT method with the estimation of the direction of motion to the extremum of the curvature function using the Haar wavelet function.

The initial data for this are: δ_1 – the error in the search for the optimum start (determined at the stage

of a priori research of the quality functional); δ_2 – the error in the search for the optimum of the applied problem.

Step 1. The following are set: $c[0]$ – initial approximation to the optimum coordinate in the first period; $\gamma[1]$ – step; a – WF discretization step; s_1 – the length of the carrier WF first start $\Psi_1(i)$; Δ_s – the step of changing the length of the WF $\Psi_1(i)$ carrier when determining the range of coordinates of the extremum; start number $k = 1$; iteration number $n = 1$; A_1 – value of the minimum amplitude of the recorded extremum; ΔR – the initial approximation to the value of the duration of the interval between the recorded extremes.

Step 2. The direction of the search is estimated by (2) at the point of approximation to the optimum coordinate for start k . For this, the weighted sum with the Haar WF (at the point at) is used). The length of the carrier for the WF is determined in the analysis of the objective function. The integral nature of such airspace allows one to reduce sensitivity to local extremes and to distinguish a segment of the objective function, where, as studies have shown, the signal maximum is most likely to be found in the studied period. At this stage, the mark of evaluation is checked according to (3)

$$G_{jk} = \frac{1}{S_k} \sum_{\substack{i=-\frac{s_k}{2} \\ i \neq 0}}^{\frac{s_k}{2}} Q(x[n], c_j + ia) \cdot \Psi_k(i).$$

In the case of a sign change, on the basis of the known property of estimates of the direction of the search on the basis of the gradient, change the sign when crossing the optimum, at this stage the range of changes in the coordinates of the extremum is determined as $c[n-1] \leq c^* < c[n]$.

Step 3. The search is performed for the optimum coordinate ranges $Q(x, c)$ by (1) at k until the end of the data sequence being studied, otherwise it will stop.

Step 4. The coordinate of the extremum in the study period is assigned a value $c^* = c[n-1]$.

Step 5. The value $Q(x, c^*)$ is compared with A_1 . If $Q(x, c^*) \geq A_1$, the coordinate of the period extremum is recorded as RR [kk] and its coordinate as cc[kk] (here kk is the number of the period under study in the sequence).

Step 6. The length of the carrier s_k is compared with half the length of the interval between the extrema: when $s_k \leq \frac{\Delta R}{2}$ the carrier length of the WF is determined as $s_{k+1} = s_k + \Delta_s$; when the length of the WF $s_k > \frac{\Delta R}{2}$, carrier to search for the extremum of the next period is determined as s_1 . In this case, due to the integral nature of the Haar WF, as the carrier wave length increases, the coordinate of the next search step shifts to the extremum of the next period. If the length of the carrier exceeds half the length of the period at a subsequent extremum with smaller amplitude than the previous one, the search may go in the wrong direction.

Step 7. The initial approximation to the coordinate of the extremum of the next period is determined as with $c[n] = c[kk]$ and the transition to step 2.

Method for determining of the ECG characteristic points and the intervals between them

The main stage of determining of R-peaks and intervals between them at multi-start optimization with wavelet transform based are given below.

Stage 1. Wavelet transform of the analyzed ECG signal. To reduce the noise level of the ECG signal, when searching R-peaks with preserving information about the frequency and spatial localization of QRS-complexes during automated processing and taking into account the recommendations [21], the Dobeshi WF is used in the work.

Stage 2. Determination of the spatial coordinates of R-peaks by searching for the coordinates of the extrema of periodic signals using the developed method. The signals from the MIT / BIH Arrhythmia Database [22] were investigated as such signals.

Stage 3. Determination of the intervals between the R-peaks for the subsequent evaluation of the statistical characteristics of the ECG signals, classification and diagnostic decision making.

The main steps of the MOWT method are described above. In the initial data the following are additionally specified: Δ_s – step for changing the length of the WF carrier $\Psi_1(i)$; A_1 – threshold value of the amplitude of the extremum; ΔR – initial approximation to the length of the interval between extrema.

The determination of the coordinates of the extrema is carried out in this sequence.

Step 1. Search for R – extrema (R – peaks) (Fig.1).

Step 1.1. When searching for R – peaks, the starting length of the WF carrier is $s_1 = 3$.

Step 1.2. The analysis is carried out in accordance with (1) with the assessment of the sign of the WT before the end of the signal under study. When the value of the WT sign changes, $Q(x, c^*)$ it is compared to A_1 .

Step 1.3. The condition $Q(x, c^*) \geq A_1$ is checked. If $Q(x, c^*) \geq A_1$ - the amplitude of the extremum of the period and its coordinate are recorded.

Step 1.4. The carrier length of the wavelet function is determined for further search the extremum. When $s_k \leq \frac{\Delta R}{2}$ the length of the carrier WF

$s_{k+1} = s_k + \Delta_s$; when $s_k > \frac{\Delta R}{2}$ the length of the

WF carrier for the next period is determined as s_1 and the transition to step 1.2 is carried out.

Step 2. Search for Q – signal extremes.

Step 2.1. When searching for Q – minima, the starting length of the WF carrier $s_1 = 2$.

Step 2.2. The starting point of the search for Q – extremum in the interval is defined as $R = R - 4$ (here R is the coordinate of the R peak obtained in step 1) and the signal is analyzed according to (1) in order to evaluate the sign of the WT.

Step 2.3. If the WT sign changes, the we are fixed amplitude and the Q-extremum coordinate, the interval number is increased by 1, and search return to step 2.2.

Step 3. Search for S – extrema (minima) (Fig.1) of signals.

Step 3.1. When searching for S – minima, the starting length of the WF carrier is $s_1 = 2$.

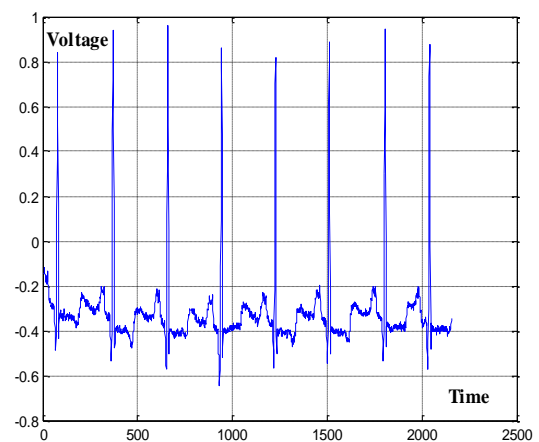
Step 3.2. The starting point of the search is S - extremum in the interval with $R = R + 5$ (here R is the coordinate of the R-maximum (obtained in step 1)) and the signal is analyzed according to (1) in order to evaluate the sign of the WT.

Step 3.3. If the WT sign changes, the amplitude and the S – extremum coordinate are fixed, the interval number is increased by 1, and go to step 3.2.

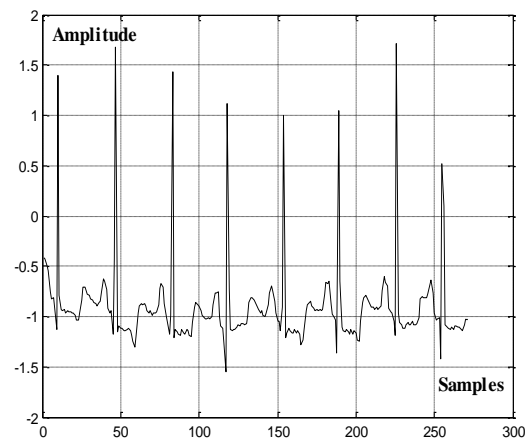
Step 4. Determine the coordinates and amplitudes P and T of the extrema (similar to steps 2 and 3).

The developed algorithm was investigated in the analysis of electrocardiogram signals with the MIT / BIH Arrhythmia Database [22].

The relative errors in the determination were as follows. Relative errors for the coordinates of R-peaks no more than 1.4 %, for the coordinates of P-peaks they are no more than 1.6 %, for the coordinates of T-peaks no more than 1.7 %, for the coordinates of Q and S troughs no more than 1.2 %, for the length of RR intervals – no more than 2.4 % are. In the study of noise immunity, the relative error in determining the length of the RR intervals is less than 4 % at a signal-to-noise ratio in amplitude of 20 ... 10.



a



b

Fig. 4. ECG signal at different stage of analysis: a) input ECG signal; b) approximation coefficient at 3 level of WF Daubechies 1

Conclusions. The paper presents a method for determining the coordinates of the extremums of non-stationary periodic signals based on multistart

optimization with wavelet transform. The procedures for evaluating the determination of the coordinates of the PQRST peaks and the intervals between them for electrocardiograms, which are based on this method of multi-start optimization with wavelet transform, are presented. The error in estimating the duration of the intervals in the studied set of signals under the conditions of the noise is investigated. The relative error in the duration of the intervals between R – peaks was less than 4 % for a signal to noise ratio in amplitude of up to 10. For the well-known Pan – Tompkins algorithm, this value is at least 5 % [25; 27-28].

Relative errors for the coordinates of R-peaks not more than 1,4 %, for the coordinates of P-peaks – no more than 1,6 %, for the coordinates of T-peaks – no more than 1,7 %, for the coordinates of Q and S troughs – no more than 1,2 %.

Thus, we can conclude that the developed method for the coordinates of extremums determining has an noise immunity and error which meets the requirements of this applied task.

These results allow us to recommend the developed method for decision support systems information technology, including telemedicine, in conditions of increasing noise level in the ECG signal.

With further research, it is planned to develop a methodology for the remaining parameters of the QRS ECG complexes, assess the influence of the magnitude of $\gamma^{[n]}$ on the efficiency and eliminate the influence of edge effects on determining the coordinates of the extremums.

References

1. Bezuglov, D. & Shvydchenko, S. (2011). “Informacionnaya tehnologiya veyvlet differencirovaniya izmereniya rezultatov na fone shumov” [Information technology of wavelet differentiation of measuring result on the noise background], *Herald of computers and information technologies*, (6 (84)), pp. 42-45 (in Russian).
2. Boronoyev, V. & Garmayev, B. (2012). “Issledovaniye statisticheskoy modeli komponentov signala davleniya” [Research of the Statistical Model of Pressure Signal Components], *Herald of Buriat State university*, (3), pp. 217-219 (in Russian).
3. Dubrovin, V. & Shchedrina, T. (2010) “Sistema avtomatizirovannogo analiza electrocardiogram, osnovannaya na veyvlet tehnologiyah” [Automated Analysis System of Electrocardiogram Based on the Wavelet Technology], *Artificial Intelligence*, (4), pp. 190-194 (in Russian).
4. Kutluk, A., Shiba, K. & Tsuji, T. (2016). “Evaluation of Autonomic Nervous Activity Based on Arterial Wall Impedance and Heart Rate Variability”, pp. 469-474. – Available at http://bsys.hiroshima-u.ac.jp/pub/c/c_160.pdf. – Active link – 9.06.20.
5. Fotiadis, D., Likas, A., Michalis, L. & Pappaloukas, C. (2009). “Electrocardiogram (ECG): (Automated diagnosis)”, *Wiley Encyclopedia of Biomedical Engineering*, pp. 10-17.
6. (2020). “SCHILLER ECG Measurement and Interpretation Software for Children and Adult ECGs” [Digital Resource]. – Available at: https://www.schiller.ch/en/ECG_Interpretation. – Active link – 9.06.20.
7. (2020). “SAECG Analysis ECGs” [Digital Resource]. – Available at: https://www.schiller.ch/en/SAECG_Analysis. – Active link – 10.06.20.
8. (2020). “Heart Rate Variability” [Digital Resource]. – Available at: <https://www.schiller.ch/en/HRV>. – Active link – 10.06.20.
9. (2020). “Marquette 12SL ECG analysis program” [Digital Resource]. – Available at: https://www.www3.gehealthcare.co/Marquette_12SL_ECG_Analysis. – Active link – 9.06.20.
10. (2020). “GE Healthcare Cardiosoft” [Digital Resource]. – Available at: https://www3.gehealthcare.in/en/Products/Categories/Diagnostic_ECG/tress_Testing/cardiosoft. – Active link – 9.06.20.
11. (2020). “Fukuda Denshi Resting ECG Software” [Digital Resource]. – Available at: <https://www.fukuda.com>. – Active link – 9.06.20.
12. Siniutin, S. (2012). “Obrabotka elektrocardiogram s pomoshchiyu veyvlet analiza v monitoringe Holtera” [Electrocardiograms processing with wavelet analysis help in Holter’s monitoring], *Computers and Information Technologies in science, engineering and control, Izvestiya TRTU*, pp. 52-57 (in Russian).
13. Gayani, K. S., Vinodkumar, Jacob & Kavitha, Nair. (2014). “Automation of ECG heart beat detection using Morphological filtering and Daubechies wavelet transform”, *International or-*

ganization of Scientific Research Journal of Engineering (IOSRJEN), (04 (12)), pp. 53-58.

14. Daubechies, I. (1992). "Ten Lectures on Wavelets", *CBMS-NSF Lecture Notes*, No. 61.

15. Grigoriev, D. & Spicyn, V. (2012). "Application of Neural Net and Discrete Wavelet Transform for Electrocardiograms analysis and classifications", *Control, Calculation Technique and Informatics*, (321 (5)), pp. 57-61.

16. Gazizianova, V., Bulashova, O., Khazova, E., Nasybullina, A. & Malkova, M. (2016). "Variablnost serdechnogo ritma u pacientov s shronicheskimi zabolevaniyamy i shronicheskimi obstructivnymi zabolevaniyamy legkish" [Heart Rate Variability in patients with Chronic Failure and Chronic Obstructive Pulmonary Disease: Clinical Parallels], *Kazan Medical magazine*, (3), pp. 421-425 (in Russian).

17. Omar, M. & Mohamed, A. (2011). "Evaluation of Morphological Characterization of the Long-Record ECG Signal and its HRV for Congestive Heart Failure", *The Online Journal on Computer and Information Technology (OJCSIT)*, (2(1)), pp. 107- 110.

18. Krylov, V. & Shcherbakova, G. (2008). "Ierarchicheskii subgradientniy iterativniy metod optimizacii v prostranstve veyvlet preobrazovaniya" [Ierarchical sub – gradient iterative optimization method in the wavelet transforming space], *Electronics and Communications*, (6 (47)), pp. 28- 31 (in Russian).

19 Shcherbakova, G. & Krylov, V. (2009) "Adaptive clustering in hyperbolic wavelet domain", *IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, 21-23 September 2009, Rende (Cosenza), Italy, pp. 400-403.

20. Gonzales, R. C. & Woods, R. E. (2002). "Digital image processing", Second Edition, *Pearson education, Inc. Prentice Hall*, 1072 p.

21. Anshul, Jain, Yamini Goyal & Ajit Patel. (2012). "ECG Analysis System with Event Detection based on Daubechies Wavelet", *International Conference on Electronics Engineering and Infor-*

matics (ICEEI 2012), Singapore, Vol. 49, pp. 145-149.

22. (2019). MIT/BIH Arrhythmia Database. Available from: <http://physionet.org/physiobank/database/mitdb/>. – Active link – 9.06.19.

23. Feyzilberg, L. (2016). "Intellectualniye vozmognosti I perspektivy razvitiya fazagrafia – informacionnoy tehnologiyi obrabotki signalov slognoy formy" [Intellectual possibilities and perspective of phase graphic development – information technology of the complicate signal processing], *Cybernetics and calculation technique*, (186), pp. 56-77 (in Russian).

24. Povorozniuk, A. I. & Filatova, A. E. (2016). "Razrabotka systemy alternativnykh diagnosticheskikh priznakov v kardiologicheskikh sistemakh poddergki priniatiya resheniy" [The work out of the alternative diagnostic signs in the cardiologic decision support system], *East-European journal of the advanced technologies*, (81), pp. 3-9.

25. Kramarenko, A. V. & Kramarenko, Y. A. (2016). "Svertocno-korrelatsionniy algoritm vydeleniya QRS kompleksov" [Convolutional correlation allocation algorithm of QRS complexes] – Available at: <https://www.tredex-company.com>. – Active link – 9.06.20.

26. Pavlovich, R. V. (2016). "Vseukrainskaya telemedizinskaya seti distancionnoy EKG diagnostiki "Telekard"". – Available at: <https://www.tredex-company.com>. – Active link – 9.06.20.

27. Pan, J. & Tompkins, W. J. (1985). "A real-time QRS detection algorithm", *IEEE Transactions on biomedical engineering*, Vol. BME-32, (3).

28. Sedghamiz, H. (2014). "Matlab Implementation of Pan Tompkins ECG QRS detector". – Available at: https://www.researchgate.net/publication/313673153_Matlab_implementation_of_Pan_Tompkins_ECG_QRS_detect. – Active link. – 9.06.20.

Received 15.03.2020

Received after revision 25.05.2020

Accepted 15.06.2020

УДК 004.021

¹**Щербакова, Галина Юрїївна**, д-р технїч. наук, доцент, професор кафедри інформаційних систем, E-mail: Galina_onpu@ukr.net, ORCID: 0000-0003-0475-3854

¹**Крилов, Віктор Миколайович**, д-р технїч. наук, професор, професор кафедри прикладної математики та інформаційних технологій, E-mail: Viktor_Kriylov@gmail.com, ORCID: 0000-0003-1950-4690

¹**Плачинда, Ольга Євгенїївна**, канд. технїч. наук, доцент кафедри нафтогазового та хїмічного машинобудування, E-mail: olga_plach2017@ukr.net, ORCID: 0000-0003-3382-229X

¹Одеський національний політехнічний університет, пр. Шевченка, 1, м.Одеса, Україна, 65044

ВИЗНАЧЕННЯ ХАРАКТЕРНИХ ТОЧОК ЕЛЕКТРОКАРДИОГРАМ З ДОПОМОГОЮ МУЛЬТИСТАРТОВОЇ ОПТИМІЗАЦІЇ З ВИКОРИСТАННЯМ ВЕЙВЛЕТ-ПЕРЕТВОРЕННЯ

***Анотація.** Приведений опис основних етапів методу визначення координат нестационарних періодичних сигналів. Цей метод заснований на мултистартовій оптимізації з використанням вейвлет-перетворення. Приведені основні етапи базової форми мултистартового методу оптимізації з використанням вейвлет-перетворення. Приведені результати дослідження завадостійкості, погрїшності пошуку екстремуму асиметричної і мултимодальної тестових функцій. Основні етапи пошуку екстремуму з використанням цього методу використані для визначення координат екстремумів нестационарних періодичних сигналів. Цей метод використаний для діагностування на базі електрокардіограм у телемедицині. Цей метод дозволив визначити координати характерних фрагментів для електрокардіограм. Методика оцінки координат цих характерних фрагментів електрокардіограм та інтервалів між ними заснована на мултистартовій оптимізації з використанням вейвлет-перетворення. Описані основні етапи цієї методики. Проведена оцінка погрїшності оцінки довжини інтервалів між характерних фрагментів і оцінено завадостійкість такої оцінки при зростанні рівня шумів. Відносна погрїшність визначення довжини інтервалів між характерними фрагментами склала менше ніж 4% при відношенні сигнал/шум по амплітуді до 10. Ці результати дозволяють рекомендувати розроблений метод для використання в інформаційних технологіях для автоматизованих систем підтримки прийняття рішень в різних областях, уключаючи телемедицину, в умовах зростання рівня завад ЕКГ сигналу. Для подальших досліджень планується розробити методологію оцінки інших параметрів QRS і PT комплексів в ЕКГ, знижуючи вплив крайових ефектів при оцінці координат екстремумів.*

***Ключові слова:** мултистартова оптимізація; вейвлет-перетворення; електрокардіограма; аритмія; діагностика*

УДК 004.021

¹**Щербакова, Галина Юрьевна**, д-р технїч. наук, доцент, професор кафедри информационных систем, E-mail: Galina_onpu@ukr.net, Scopus ID: 27868185600, ORCID: 0000-0003-0475-3854

¹**Крылов, Виктор Николаевич**, д-р технїч. наук, професор, професор кафедри прикладной математики и информационных технологий, E-mail: Viktor_Kriylov@gmail.com, Scopus ID: 16202975800, ORCID: 0000-0003-1950-4690

¹**Плачинда, Ольга Евгеньевна**, канд. технїч. наук, доцент кафедри нефтегазового и химического машиностроения, E-mail: olga_plach2017@ukr.net, ORCID: 0000-0003-3382-229X

¹Одесский национальный политехнический университет, пр. Шевченко, 1, м. Одесса, Украина, 65044

ОПРЕДЕЛЕНИЕ ХАРАКТЕРНЫХ ТОЧЕК ЭЛЕКТРОКАРДИОГРАММ С ПОМОЩЬЮ МУЛЬТИСТАРТОВОЙ ОПТИМИЗАЦИИ С ИСПОЛЬЗОВАНИЕМ ВЕЙВЛЕТ-ПРЕОБРАЗОВАНИЯ

***Аннотация.** Приведено описание основных этапов метода определения координат нестационарных периодических сигналов. Этот метод основан на мултистартовой оптимізації с использованием вейвлет-преобразования. Приведены основные этапы базовой формы мултистартового метода оптимізації с использованием вейвлет-преобразования. Приведены результаты исследования помехоустойчивости, погрїшности поиска экстремума асиметричной и мулти-модальной тестовых функций. Основные этапы поиска экстремума посредством этого метода применены для определения координат экстремумов нестационарных периодических сигналов. Этот метод применен для диагностики электрокардиограмм в телемедицине. Этот метод позволил определить координаты характерных фрагментов для электрокардиограмм.*

Методика оценки координат этих характерных фрагментов электрокардиограмм и интервалов между ними основана на мультистартовой оптимизации с использованием вейвлет-преобразования. Описаны основные этапы этой методики. Проведена оценка погрешности оценки длительности интервалов между характерными фрагментами и оценена помехоустойчивость такой оценки при возрастании уровня шумов. Относительная погрешность длительности интервалов между характерными фрагментами составила менее 4 % при отношении сигнал/шум по амплитуде до 10. Эти результаты позволяют рекомендовать разработанный метод для применения в информационных технологиях для автоматизированных систем поддержки принятия решений в различных областях, включая телемедицину, в условиях возрастания уровня помех ЭКГ сигнала. Для дальнейших исследований планируется разработать методологию оценки остальных параметров характерных фрагментов и комплексов в ЭКГ, снижая краевые эффекты при оценке координат экстремумов.

Ключевые слова: мультистартовая оптимизация; вейвлет-преобразование; электрокардиограмма; аритмия; диагностика



Shcherbakova, Galina Y.

Research field: pattern recognition, optimization, technical diagnostics, medical diagnostics



Krylov, Viktor N.

Research field: pattern recognition, optimization, segmentation, technical diagnostics, medical diagnostics



Plachinda, Olha E.

Research field: computer aided design systems