The object of this study is the process of automated analysis of the electrocardiographic signal (ECS) during long-term monitoring in real time, carried out by mobile wireless systems.

The study considers the problem related to the insufficient accuracy of automated diagnostics during long-term monitoring of the electrocardiogram (ECG) under conditions of limited computing resources and the presence of noise.

A modified Pan-Tompkins algorithm for determining the boundaries of the QRS system has been developed. Based on this algorithm, the PCard software module for the hardware and software system was implemented, enabling high-quality automated diagnostics both under the standard mode and during long-term ECG monitoring in 12 leads in real time. The PCard software module allows for ECG registration, digital filtering, measurement and calculation of electrocardiographic parameters, automatic determination of diagnostic criteria and diagnostic conclusions, formation of a general diagnostic conclusion of ECG, as well as medical processing of ECG.

The high quality of the diagnostic analysis was confirmed by the obtained accuracy rates of the algorithm for determining normal complexes – 99.99%, for determining ventricular complexes – 99.90%, for determining various pathologies – 98.43%. The ECG processing time was about 4.7 seconds for a 40-minute record. The proposed method for determining the boundaries of QRS complexes is based on the finite difference method, which distinguishes it from common methodologies using spectral analysis, wavelet transforms, or Fourier transforms. This methodology simplifies determining the parameters of the basic ECG elements and significantly reduces the amount of calculations, which generally increases the processing time and reduces the required volume of system resources

Keywords: electrocardiogram, Holter monitoring, automated analysis, Pan-Tompkins algorithm, ESP32, QRS complex

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AUTOMATED REAL-TIME ELECTROCARDIOGRAM DIAGNOSIS BASED ON THE MODIFIED PAN-TOMPKINS ALGORITHM FOR LONG-TERM MONITORING SYSTEMS

Yuliya Gerasimova
Candidate of Engineering Sciences*
Fatimah Sidi
PhD
Department of Computer Science***
Victor Ivel
Doctor of Sciences in Engineering
Department of Energetic and Radioelectronics
Manash Kozybayev North Kazakhstan University
Pushkin str., 86, Petropavlovsk, Republic of Kazakhstan, 150000
Vladimir Avdeyev
Candidate of Engineering Sciences*
Lili Nurliyana Abdullah
PhD
Department of Multimedia***
Sayat Moldakhmetov
Corresponding author
PhD
Department of Power Engineering and Radio Electronics**
E-mail: ssmoldahmetov@ku.edu.kz
*Department of Energetic and Radioelectronics**
**Manash Kozybayev North Kazakhstan University
Pushkin str., 86, Petropavlovsk, Republic of Kazakhstan, 150000
***University of Putra Malaysia
Universiti str., 1, Selangor, Malaysia, 43400

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1. Introduction

Cardiovascular diseases (CVDs) are the leading cause of death in the world [1], so the development of effective technologies that enable the detection of early stages of cardiac diseases is one of the most important tasks of modern medicine.

Automated analysis of electrocardiological signals always requires a special software algorithm for morphological analysis of ECG. Currently, market offers a wide variety of software for mobile devices with automated analysis of biomedical information, including ECG. In this case, ECG analysis is carried out without the participation of a doctor, so it is the algorithm that determines the quality of diagnostics of the automated system.

The purpose of such algorithms is to determine the position of the QRS complex since this complex is an indicator of pathological conditions of the cardiovascular system [2]. The QRS complex is an ECG fragment that reflects the process of depolarization of the ventricles of the heart, that is, the electrical activity accompanying their contraction. It consists of three successive waves (Q, R, and S); its shape and duration make it possible to identify various rhythm and conduction disorders. Detecting and defining the QRS complex boundaries is the first stage of automatic selection of all diagnostic features of ECG.

There are many studies aimed at finding a satisfactory universal solution for detecting QRS complexes [3]. A significant part of the work is limited to rhythm analysis only,

which does not require detailed processing of electrocardiographic signal (ECS) [4, 5]. However, for some studies (Holter monitoring systems, ECG analysis with the issuance of a full conclusion, etc.), more in-depth ECS processing is necessary. The use of autonomous wireless long-term monitoring devices operating in real time imposes additional requirements on the quality, recognition accuracy, and speed of the algorithms used. For example, a recognition percentage value of 0.1 is high enough for ECG registration under a standard mode, but for long-term monitoring it is already low since it corresponds to one hundred missed QRS complexes.

The efficiency of QRS detection methods is still insufficient when applied to wearable devices because of complicated noise interferences present in the signals. This noise can be caused by several factors, including body movement, poor electrode contact, power frequency interference in the environment, etc. [6].

In addition, many algorithms for mobile devices are designed to record ECG from a small number of leads (usually from 3 leads), which casts doubt on the reliability of the diagnostic conclusion, especially during long-term monitoring, since significant anomalies can be missed. Therefore, research aimed at developing algorithms designed for wireless 12-channel long-term monitoring devices operating in real time is relevant.

2. Literature review and problem statement

In recent years, the scientific literature has reported many approaches to the automatic detection of the QRS complex in ECG signals. Work [7] considers algorithms based on machine learning technologies (Deep Learning, DL), which allow recognition based on raw data. The main advantage of such models is their ability to automatically extract features. However, high efficiency of DL algorithms is achieved only with a large volume of high-quality training data [8]. If there is a shortage of them, such models are subject to overfitting and demonstrate low resistance to noisy signals, which limits their use in mobile and wearable devices.

In [9], methods based on wavelet transforms and morphological operations are described. In this class of algorithms, high accuracy of QRS complex detection is ensured by analyzing the time-frequency characteristics of the signal. However, these methods require significant computing resources, have a complex mathematical apparatus and, in some cases, involve a time delay [10], which renders them unsuitable for implementation in real-time systems, especially on the wearable device platform.

In contrast, the Pan-Tompkins algorithm [11] and its modifications [12] are simpler and faster processing methods based on basic mathematical operations (differentiation, integration, threshold filters). Despite their relative simplicity, they provide fairly high accuracy on clean signals. However, under noisy conditions (e.g., when the patient moves or when using compact electrodes), their efficiency is significantly reduced. For example, the original implementation of the Pan-Tompkins algorithm records an error of about 0.68% [13], which corresponds to hundreds of missed complexes. Even modified versions show limited results; for example, in [14], the data error during the study was 0.169%. In [15], the proposed algorithm is developed based on the Pan-Tompkins and Eldendy algorithm, it has a data error of 0.04% when tested on the QTDB database and 0.31% when tested on the MIT-BIH database. The MIT-BIH database includes noisy ECGs, so the accuracy of the proposed method is significantly reduced in the presence of noise, which makes it ineffective for wearable long-term monitoring devices.

The issue of the algorithm's efficiency and speed is particularly relevant in the context of long-term monitoring using autonomous wearable devices. Works [16, 17] emphasize the importance of low power consumption and minimal processing time for such applications. One of the features of the cited studies on the topic under consideration is that there are practically no publications that would describe the use of the developed algorithm in a specific software application for automated diagnostics. The authors mainly devote their works to a detailed description of the developed algorithm but do not indicate its practical implementation, especially with regard to the analysis of ECG in 12 standard leads. That also does not make it possible to verify the full effectiveness of the proposed methods.

Summarizing the review, we can highlight the following shortcomings of existing approaches to recognizing QRS complexes. Known methods based on machine learning require large volumes of high-quality labeled data and are characterized by low resistance to noise. Algorithms using wavelet transforms and morphological operations are computationally expensive and are not suitable for implementation in devices with limited resources, while classical algorithms such as Pan-Tompkins and its modifications lose accuracy in noisy or unstable signals typical for mobile or wearable ECG systems. In addition, most published studies are limited to a theoretical description of the algorithms, without their practical integration into real diagnostic software solutions, especially in the context of multi-channel ECG monitoring.

Thus, the task of developing an algorithm for recognizing QRS complexes that would provide an error of no more than 0.1% under high-noise conditions and would not require significant computational resources remains unsolved. An additional problem is the lack of comprehensive solutions that include not only a description of the algorithm but also its practical implementation in long-term ECG monitoring systems. Addressing these issues is especially important for wearable medical devices, which have performance and power limitations and require sufficient speed to analyze 12-lead ECG in real time.

3. The aim and objectives of the study

The aim of our study is to modify the Pan-Tompkins algorithm for determining the boundaries of the QRS complex in the long-term monitoring and automatic ECG analysis system in such a way as to ensure high-quality diagnostics under the long-term and standard recording modes of bioelectrical potentials of the heart in 12 leads. This would improve the accuracy and efficiency of cardiovascular disease diagnostics, minimize the influence of the human factor in interpreting the results, and expand the capabilities of using long-term monitoring systems in outpatient and remote settings.

To achieve this aim, the following objectives were accomplished:

– to improve the key stages of the original Pan-Tompkins algorithm, which limit the quality of diagnostics and lead to an increase in processing time;

– to implement software for a hardware-software system with the integration of the developed algorithm and verify

it experimentally on real ECG recordings in 12 leads during long-term and standard monitoring to assess the accuracy and speed of processing.

4. The study materials and methods

The object of our study is the process of automated analysis of the electrocardiographic signal during long-term monitoring in real time, carried out by mobile wireless systems.

The hypothesis of the study suggests that the use of a highly accurate and faster algorithm for recognizing QRS complexes will make it possible to design a software module for a mobile complex that provides high-quality automated ECG analysis during long-term monitoring in real time.

When developing the QRS complex recognition algorithm in this study, the Pan-Tompkins algorithm was used as a basis, which is one of the most well-known and widely used methods for determining QRS complexes. It includes the stages of filtering, numerical differentiation, squaring the derivative, integration, and then threshold detection. Despite its simplicity and relatively high efficiency on clean ECG signals, the algorithm has a number of significant limitations. These include reduced accuracy under high noise conditions (patient movements, electrode interference), fixed filter parameters, non-adaptive width of the integration windows, and the lack of support for synchronous analysis of several leads. These shortcomings make it less suitable for use in modern mobile and wearable long-term monitoring systems, where speed, noise immunity, and limited computing resources are critical. Elimination of these shortcomings became the basis for developing a new algorithm for determining the boundaries of the QRS complex and using it in wearable devices.

To prove and implement this hypothesis, a specialized bench (Fig. 1) was designed and manufactured as part of the experiments, including a mobile hardware and software cardio complex, measuring tools, and auxiliary components. The bench is designed to configure and demonstrate the operation of an automated complex for wireless transmission and analysis of ECG signals.

The setup includes an SKX-2000 electrocardiogram generator, which is capable of generating ECG signals without pathology, with pathology, and signals combined with interference. A variety of input signals makes it possible to configure the algorithms of hardware and software filters, test the operation of the ECG diagnostics software module. A Hantek 1008 multichannel oscilloscope and a Beelink minicomputer were used to display biomedical transmitted and received signals. The horizontal panel of the setup contains hardware elements of the wireless biomedical information transmission system (Fig. 2). These include: AD8232 biomedical amplifiers, Wi-Fi transmitter. and Wi-Fi receiver boards.

The I2C interface, DAC (12-bit) of the auxiliary boards of the Arduino DUE modules [18] are used to display on the monitor screen and preliminarily analyze the output digital signals of the ESP32-S2 modules. The Joulescope JS220 precision meter was used to measure the energy consumption by the ECG information transmission unit. The monitor screen shows information about the energy consumption of the autonomous Wi-Fi transmission subsystem of ECG signals: consumption current – 49.43 mA, supply voltage – 3.3 V, power consumption – 163.78 mW.

Fig. 2 shows the structural diagram of the hardware and software of the mobile electrocardiocomplex, which is part of the specialized bench.

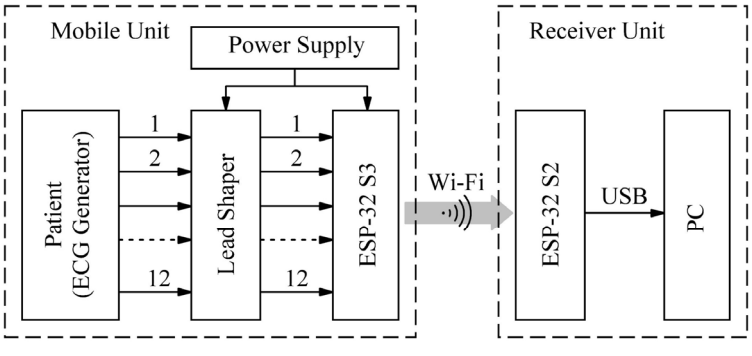


Fig. 2. Cardiocomplex for transmission and analysis of electrocardiographic signals

The following designations are used in Fig. 2:

– AD8232B amplifier lead shaper (LS);

– power supply unit on Li-ion 18650 batteries;

– ESP32-S3– Wi-Fi transmitter module on ESP32-S3 board;

– ESP32-S2– Wi-Fi receiver module on ESP32-S2 board;

– PC – personal computer.

The following software is installed on the personal computer, which is part of the test bench, to ensure interaction with the hardware and signal analysis:

– Arduino IDE – for loading firmware onto ESP32 and Arduino DUE modules;

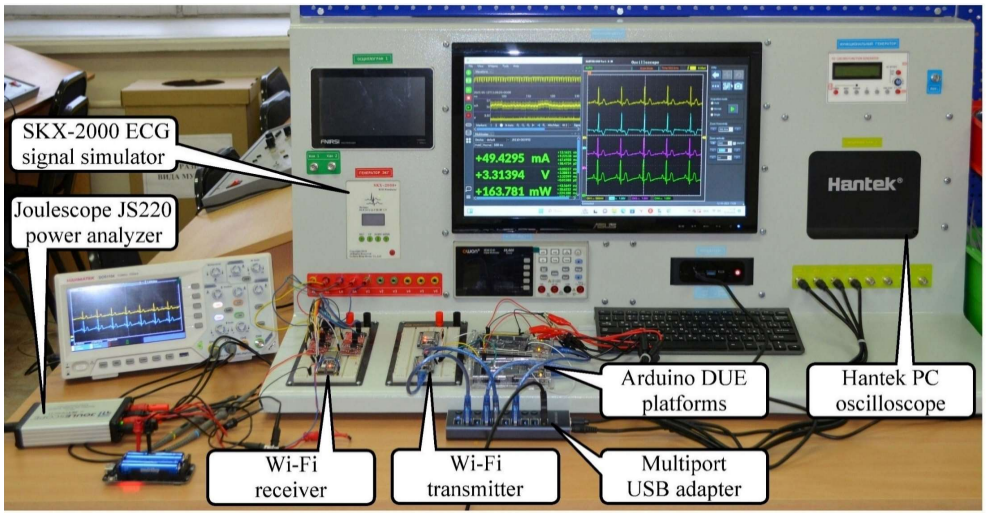


Fig. 1. Specialized ECG bench

– Hantek software – for visualizing analog signals from an oscilloscope;

– Joulescope software – for monitoring the energy consumption of the wireless data transmission module;

– PCard software module – our own development, providing automated processing, analysis, and diagnostics of ECG in 12 standard leads.

ECG signals are acquired from the patient (from the SKX-2000C+ generator) and then sent to LS unit, which includes 12 biomedical amplifiers. From the LS unit output, the amplified ECG signals are sent to the Wi-Fi transmitter module, digitized, filtered, and transmitted as data packets [19]. The Wi-Fi receiver module receives data and transmits them to the PC, where the ECG is analyzed and a diagnostic conclusion is formed.

In this study, the Russian Society of Holter Monitoring and Non-Invasive Electrophysiology (ROSHMNE) databases were used to test the algorithm and the PCard software module as a whole. The check was performed on the ROSHMNE 2006 long-term ECG test database and the ROSHMNE 2018 "ECG in 12 standard leads" test database. The test databases are freely available [20]. The ROSHMNE software package contains an ECG test database and a program for assessing the correctness of computer diagnostics. The test database is intended for use by manufacturers of electrocardiographs with the option of computer ECG analysis.

5. Results of studying the system for wireless transmission and automated analysis of electrocardiograms

5. 1. Improvement of the Pan-Tompkins algorithm for identifying the QRS complex in real-time systems

Automated ECG processing, in the case of remote monitoring using wireless communication, can consist of the following stages:

1. Digitizing the ECG of several leads in a given time interval with the required signal discreteness.

2. Compression of the received data and transmission of information via wireless communication.

3. Receiving via wireless communication and restoring data on a PC.

4. Digital filtering and signal normalization.

5. Determining the boundaries of characteristic ECG elements (QRS complexes, P and T waves, etc.).

6. Calculating RR intervals.

7. Determining extrasystoles and other "ectopic" complexes.

8. Analysis of the ECG heart rhythm.

9. Determining the magnitude of the decrease and increase in ST segments.

10. Displaying the monitored parameters on the screen.

11. Making a decision on the "criticality" of the ECG.

Along with the importance of the completeness and accuracy of the results obtained at each stage, the most "sensitive" to the reliability of the final result is the determination of the boundaries of characteristic ECG elements, in particular, the boundaries of the QRS complexes. The algorithm for determining the boundaries of the QRS complex consists of several separate tasks. First, signals are filtered, derivatives are calculated for synchronous ECG leads and summed up. After that, the results are integrated. Next, successive intervals are set within which the ECG is processed. At the next stage, the boundaries of the QRS complexes are preliminarily determined, then adjusted based on threshold values. The final stage is the final determination of the boundaries of the QRS complexes.

In the general case, after performing points 1–4, further actions are performed for a series of discrete functions $f_1(x)$, $f_2(x)$... $f_u(x)$, specified in n nodes ($n=2^{2,3\cdots}$), multiples of d and equidistant from each other with a step of h. Here u is the number of ECG leads taken synchronously.

In the Pan-Tompkins algorithm, low-pass and high-pass filters (LPF) are used at the first step of ECG processing. In the proposed algorithm, to eliminate myographic noise, network interference, isoline trend, etc., LPF and HPF were used at the stage of digital ECG filtering using wavelet transforms (point 4). The use of modern filtering methods ensures sufficient speed and makes it possible to improve the quality of ECG with minimal distortion, which is critical for its processing. In the Pan-Tompkins algorithm, ECG filtering is carried out in order to isolate characteristic ECG elements, and the filters used led to significant signal distortions.

There are several methods of numerical differentiation; in our algorithm, it is proposed to use the finite difference method, due to its simplicity and reasonable speed. According to [21], the central difference derivative over five points ($d = 5$) takes the form

$$f'(x)\approx\frac{f(x-2h)-8f(x-h)+8f(x+h)-f(x+2h)}{12h}, \quad (1)$$

where $f'(x)$ is the derivative at point x,

h is a single sample (signal sampling step).

In the Pan-Tompkins algorithm, the derivative is squared in order to enhance the ECG. For more efficient detection of QRS complex boundaries, the ECG is measured synchronously across several leads. In the proposed algorithm, the derivative values for synchronous leads are summed up by absolute value and averaged, which increases the speed of the algorithm and the accuracy of detection of QRS complex boundaries, since further actions are performed for groups of synchronous leads, and not separately for each lead. Considering that $x = kh$, where k is the number of the current node, the following expression can be written:

$$W(k/d)=\frac{1}{u}\sum_{i=1}^{u}\left|f_i'\left((k+2)h\right)\right|,$$

$$k=0,d,2d,\ldots n-d, \quad (2)$$

where $f_i'\left((k+2)h\right)-$ the derivative at the $k+2$ node of the i-th lead,

u is the number of synchronous leads,

$W(k/d)$ is the value of the averaged derivatives for the k-node.

As a result of calculations using formulas (1) and (2), an array W is obtained with a dimensionality of $p = n/d$ elements. In this case, the results of ECS processing are "compressed" by a factor of d, which increases the speed of the algorithm.

At the next step (integration), a moving average filter is used; window width w is selected empirically but is usually equal to the normal duration of the QRS complex (0.08–0.1 s), In the Pan-Tompkins algorithm, the window width is 0.15 s, which has a negative effect on its speed. To increase the speed

of the algorithm, a recursive moving average filter is used in the form

$$S_b = S_{b-1} + \frac{1}{w}\left(W(b) - W(b-w)\right), b = w+1, w+2\ldots, \quad (3)$$

where S_b is the arithmetic mean of the values of array W in the interval from $b - w$ to b,

S_{b-1} is the arithmetic mean of the values of array W in the interval from $b - w - 1$ to $b - 1$.

The current values of S_b are stored in array S taking into account the delay $w / 2$.

Fig. 3 shows the ECS plot and the results of its processing.

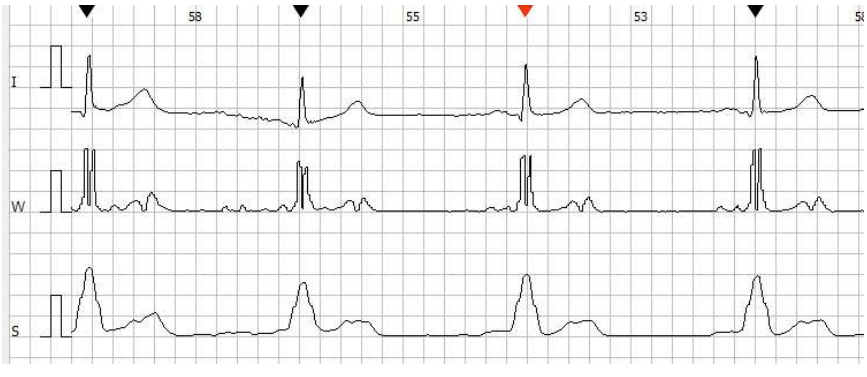


Fig. 3. Results of calculating *W* and *S*

The initial data for this algorithm were n values of the digitalized ECS with a step of $h = 0.001$ s, taken synchronously from 3 leads.

Next, at successive intervals of duration l, their local maxima M_0, M_1, ... and time values are found and saved in a two-dimensional array M, with a dimensionality of $z = n / l$.

At the next step, adjacent values of the elements of array M, the time interval between which is less than t, are deleted. This interval is calculated based on the maximum significant heart rate (HR), above which individual ECG elements are practically not determined. In this case, HR_{max} =240 bpm, then $t = 60 / 240 = 0.25$ s. In the Pan-Tompkins algorithm, $t = 0.20$ s, which corresponds to the maximum HR.

The algorithm for correcting the values of array M consists of the following steps:

1. The first element of array M is selected, and its index is assigned to the variable e_1.

2. The index of the next element is assigned to the variable $e_2 = e_1 + 1$.

3. If the index of element e_2 is outside array M, proceed to step 7.

4. If the difference between the time values of elements e_2 and e_1 is greater than t, proceed to step 6.

5. If the maximum value corresponding to e_1 is greater than the maximum value of element e_2, the maximum value of element e_2 is reset to zero (the value is deleted), and the index of e_2 is increased by one, then return to step 3, otherwise the maximum value of element is reset to zero.

6. Assign $e_1 = e_2$ and proceed to step 2.

7. A set of maximum values in array M is formed, spaced from each other by an interval of at least t.

The next step is to determine the values of the R-wave coordinates. For this purpose, further processing of ECS is carried out in successive sections of duration t_4, usually equal to four seconds. The duration of the t_4 interval determines the minimum acceptable HR for this algorithm. Considering that there must be at least three QRS complexes (two RR intervals) in an interval of 4 seconds, the following equality is valid: $HR_{min} = 60 * 2 / 4 = 30$ bpm. Further, the algorithm uses variable v – the coefficient of variability of QRS complexes, determined empirically (for this algorithm, $v = 5$). In the Pan-Tompkins algorithm, this coefficient has a similar value.

The algorithm for determining the coordinates of the "characteristic" peaks of the ECS consists of the following steps:

1. A section for ECS analysis is selected.

2. The maximum value of M_{max} in the M array is found over an interval of duration t_4.

3. All maxima that satisfy the condition $M_j > v*M_{max}$ are selected over the specified interval.

4. If the number of selected values is greater than or equal to three, proceed to step 7, otherwise these may be extrasystoles or artifacts, which are excluded at the next step.

5. A new maximum value of M_{max} is determined in the M array, excluding the values selected at the previous step.

6. All maxima that satisfy the condition $M_j > v*M_{max}$ are selected over the specified interval, while previously excluded maxima are included in the selection.

7. The obtained values of the R-wave coordinates are sequentially saved in the R array.

8. Actions of steps 1–7 are performed for all consecutive sections of ECS.

9. As a result of the algorithm, an R array of ECS peak coordinates is created.

At the last stage, the boundaries of the QRS complex are found. In this variant, the boundaries of the QRS complex are determined using methods other than those in the Pan-Tompkins algorithm; however, the proposed method ensures more reliable determination of the boundaries of the QRS complex and is implemented using the following algorithm:

1. The coordinate value of the first "characteristic" peak of the pacemaker is selected from the R array and this value is assigned to variable R_m.

2. Then, the maximum boundaries of the QRS complex are set, an indentation is made to the left and to the right of R_m by the z interval corresponding to half the maximum width of the QRS complex (in this case, $z = 0.12$ s).

3. To limit the search for the boundaries of the QRS complex to the left and to the right, a certain minimum (threshold) value of the averaged derivatives s_l and s_r is used.

4. The threshold value to the left of the current peak of ECS is determined. The minimum value in the R_m–z interval of array W is found and then the found value is doubled. The obtained result is taken as the threshold value to the left of s_l.

5. To the left of R_m, an indent of 1 / 2 the width of the normal QRS complex (0.04 s) is created and then, moving to the left within the R_m–z interval, it is determined in the W array less than the threshold. Then, moving to the left within the R_m–z interval, the value of the averaged derivative is determined, which meets the condition: the value in the W array of the next element that exceeds the current one. The value of the coordinate of the current element of the W array is taken as the boundary of the QRS complex on the left.

6. Similar actions (steps 4, 5) are performed to find the boundary of the QRS complex on the right.

7. Steps 1–6 are repeated for all elements of array *R*.

As a result of the actions performed in steps 1–7, a set of values for the left and right boundaries of the QRS complexes is determined, and the values of array *R* can be used to determine the RR intervals.

Intermediate results in determining the boundaries of the QRS complex can be used to determine the boundaries of the P, T waves and the ST segment. The results of determining the boundaries of the QRS complexes and RR intervals using this algorithm are shown in Fig. 4.

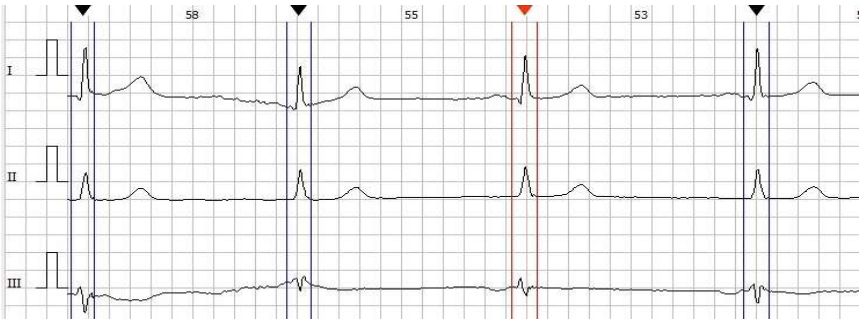


Fig. 4. Results of determining the boundaries of QRS complexes on an electrocardiogram

The input data for this algorithm were n values of the digitized ECS with a step $h = 0.001$ s, taken synchronously from 3 leads.

5. 2. Implementation of the PCard software module with the integration of a modified algorithm for automated electrocardiogram analysis

Based on the presented algorithm, the PCard software module (program) was developed. The program code was written in C++ using the Qt Greator environment. The purpose of the program is to record and automatically process ECG in 12 standard leads.

Program capabilities:

– registration and recording of ECS under a normal mode and during long-term monitoring;

– printing of selected ECS sections;

– implementing ECS filtering;

– displaying the recorded electrocardiographic leads on a computer monitor in real time;

– generating and managing internal ECG archive records and working with external archive databases;

– measuring and calculating generally accepted electrocardiographic parameters;

– automatic diagnostic conclusion;

– manual medical processing of ECG;

– obtaining a printed protocol of the patient examination.

The interface diagram and main functions of the developed program are shown in Fig. 5.

The program menu includes tabs necessary for conducting a diagnostic study of the cardiovascular system. In order to view existing ECG records obtained using the PCard program, one can use the card index.

The "ECG Archive" section contains various types of archived data. The first type of data is an archive of ECGs that were recorded using the presented cardiocomplex and the PCard software. The second type of data is an archive of ECGs obtained using other devices. And the third type is an archive of scanned ECGs. Fig. 6 shows ECG monitoring of a patient with sinus tachycardia.

ECG recording can be performed under the normal mode and under the long-term monitoring mode. To eliminate isoelectric line drift, myographic noise, network interference, and suppress high-frequency artifacts, the PCard program filters signals using a wavelet transform. The filter type is selected in the initial settings when configuring the program, but during the analysis, if necessary, one can select another filter. For this purpose, the main menu includes the "Signal Filtering" section. The window for working with filters is shown in Fig. 7. Here, the filtering parameters are selected: filter type, number of iterations, numerical values for compression and amplitude. Also in this window, one can see the filtering results for each lead.

After taking the ECG, both automatic and medical analysis can be performed. The results of automatic analysis can be represented as a diagnostic report in Fig. 8, *a*, and as a table of the results from determining the diagnostic criteria in Fig. 8, *b*.

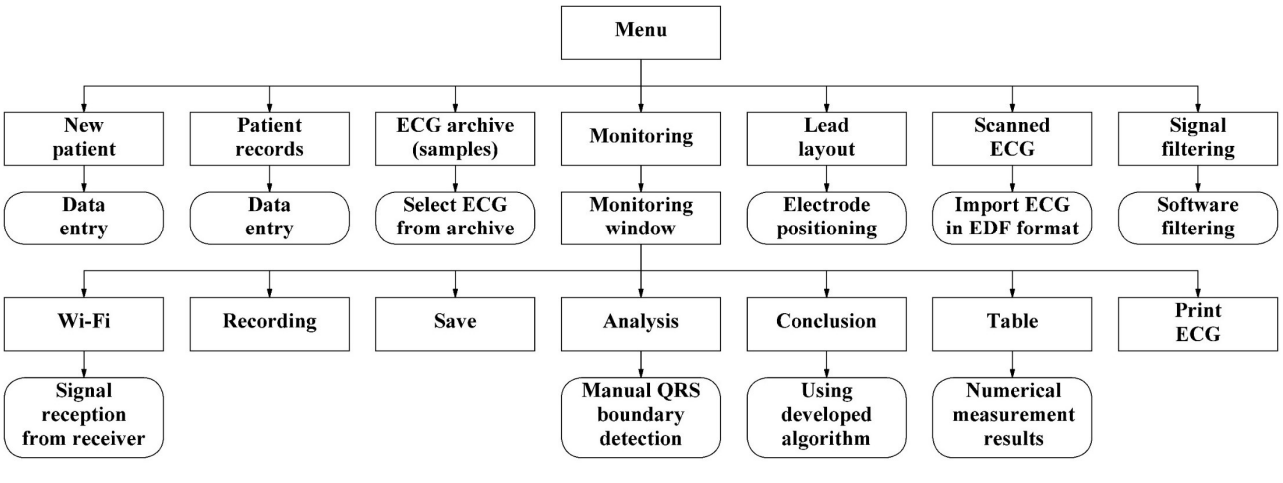


Fig. 5. User interface diagram of the program

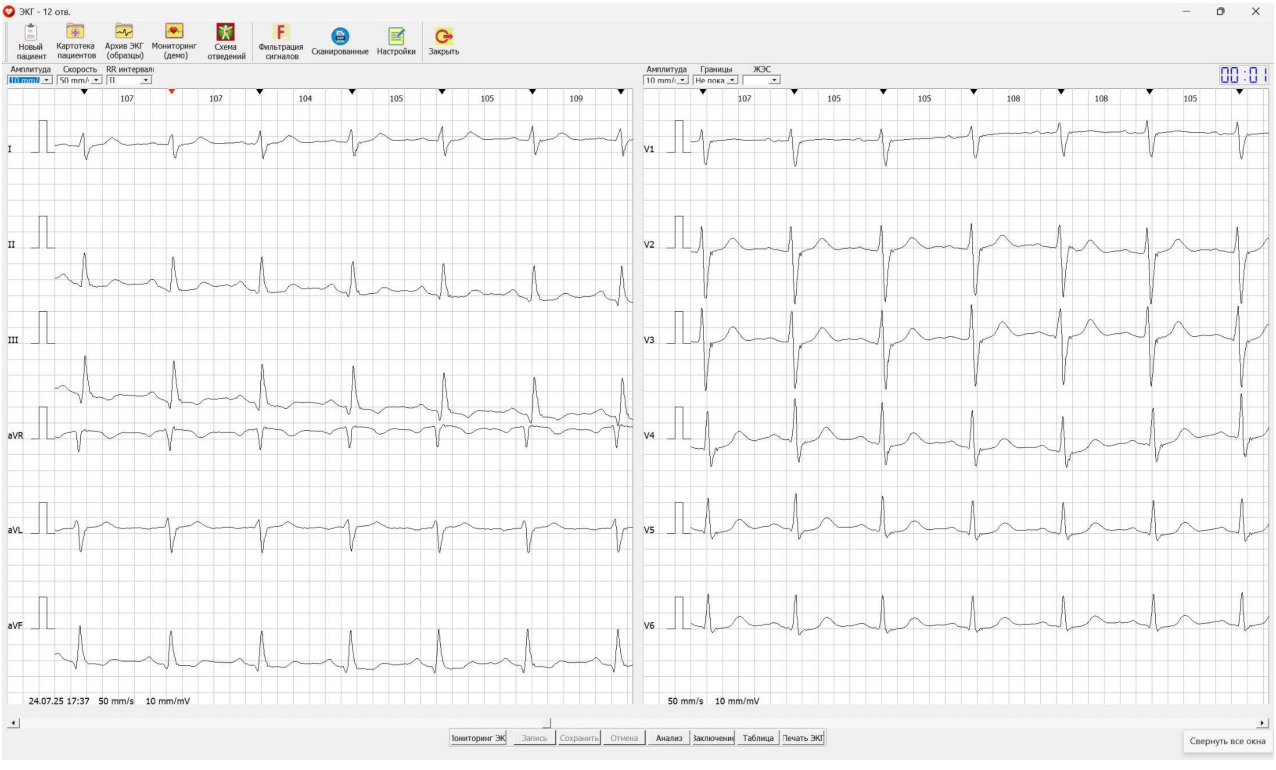


Fig. 6. Monitoring the electrocardiogram of a patient with sinus tachycardia

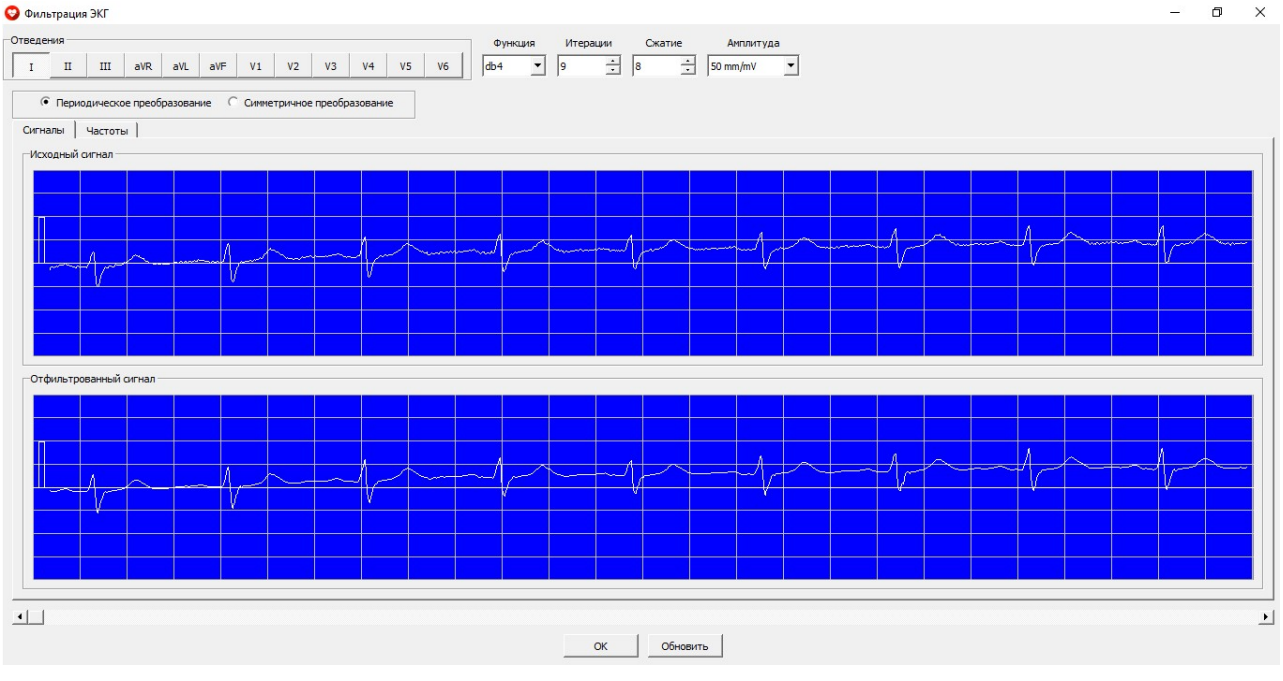
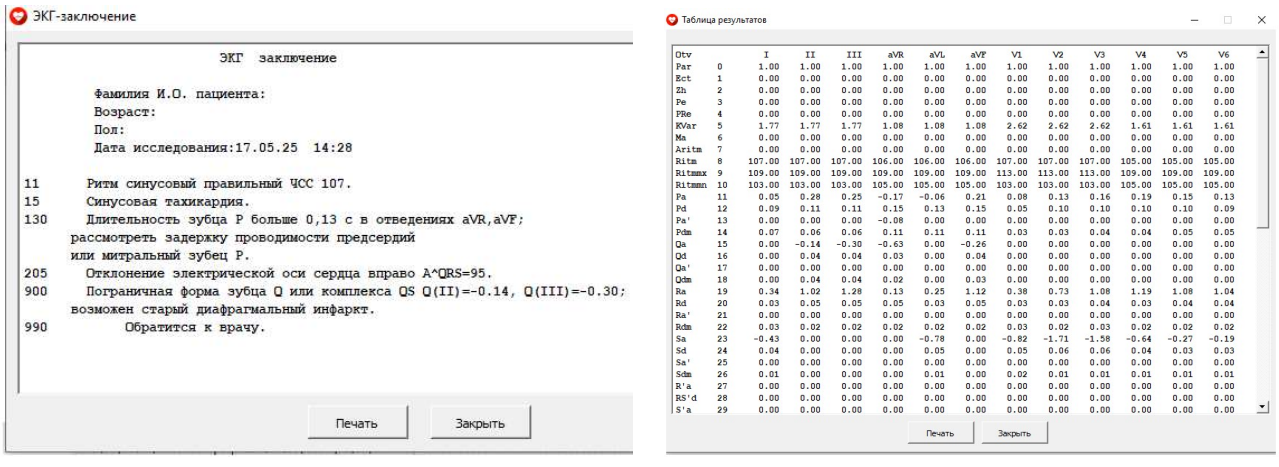


Fig. 7. Setting the electrocardiographic signal filtering parameters

The medical analysis is performed manually using the tools offered in the PCard program. ECG analysis can be performed under three modes. The “Boundaries” mode (Fig. 9) makes it possible to manually measure the duration of individual ECG sections using italics. The measured values are displayed in the corner of the window. The lower part shows the values obtained during automatic analysis. This procedure can be performed for each lead separately, or for all leads at once, using the “Synchronized leads” function.

The “Isoline” mode is used to change the position of the isoline. Detailed measurement of the amplitude and duration of all ECG elements can be performed under the “Measurements” mode. More than 300 diagnostic criteria and diagnostic conclusions were used in our program.

According to GOST 30324.2.47–2012, in order to be able to use the developed PCard program for diagnostic purposes, the algorithm on which it operates must have certain quantitative indicators that determine its performance and quality. Such indicators include sensitivity (S_{en}), specificity (P_{pn}), false alarm rate (FPR) and positive predictive value (P_{pv}), accuracy (A), algorithm error (E).



a *b*

Fig. 8. Results of automatic analysis: *a* — conclusion protocol; *b* — table obtained during automatic analysis

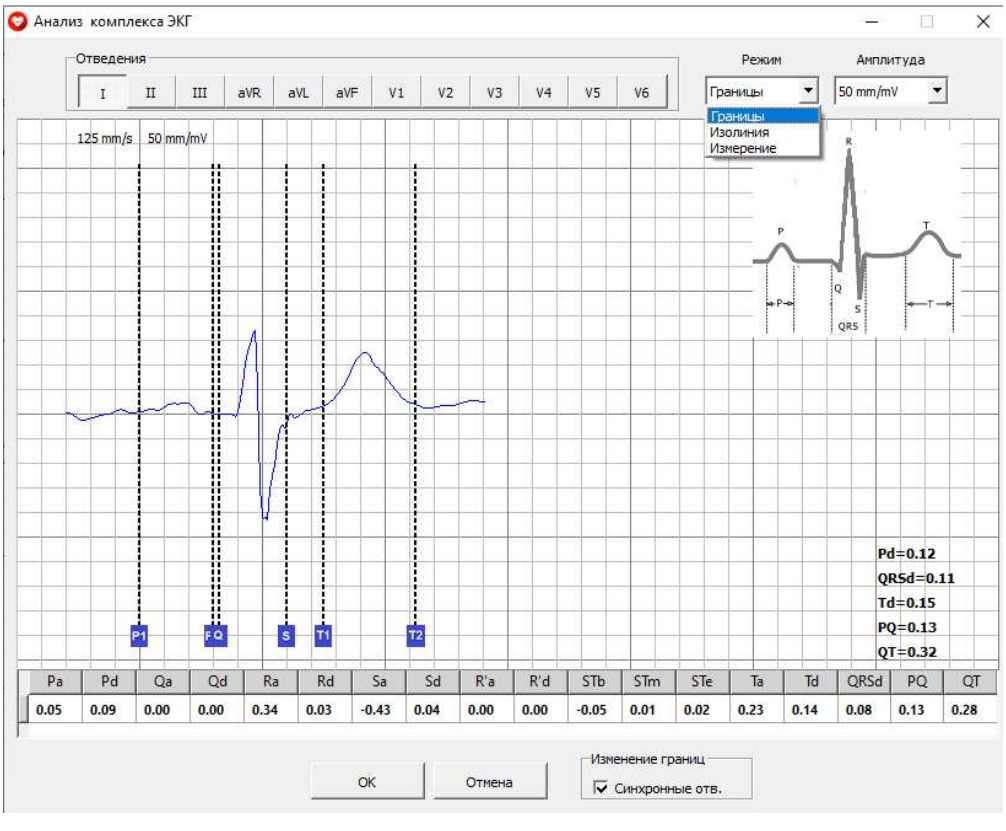


Fig. 9. Medical analysis of the electrocardiogram when selecting the "Borders" mode

Below are the formulae for calculating the listed indicators [22, 23]

$$S_{en}=\left[TR/\left(TP+FN\right)\right]\cdot 100\%, \quad (4)$$

where *TP* is the number of true positive detections (correctly detected complexes);

FN is the number of false negatives (missed complexes);

$$P_{pn}=\left[TP/\left(TN+FP\right)\right]\cdot 100\%, \quad (5)$$

where *TN* is the number of true false detections (the number of complexes in the database);

FP is the number of false detections (complexes deployed in vain):

$$FPR=\left[FP/\left(FP+TP\right)\right]\cdot 100\%, \quad (6)$$

$$P_{pv}=\left[TP/\left(TP+FP\right)\right]\cdot 100\%, \quad (7)$$

$$A=\left[TP/\left(TP+FN+FP\right)\right]\cdot 100\%, \quad (8)$$

$$E=\left[\left(FN+FP\right)/TN\right]\cdot 100\%. \quad (9)$$

The PCard program was tested on the ROHMINE test bases for ECG. The testing involves comparing the obtained

results of diagnostic conclusions of the developed PCard program with the reference files of conclusions from the ROHMINE base.

Table 1 gives the final indicators of the program testing under the long-term monitoring mode on the ROHMINE 2006 test base, where two categories were evaluated: the time of occurrence of all cardiac complexes and the selection of ventricular complexes.

Table 1

Final indicators for all ECG groups under a long-term monitoring mode

Complex ID	TN	TP	FN	FP	Sens, %	Ppn, %	FPR, %	Ppv, %	**A**	**E,** %
Normal complex	149718	149711	10	3	99.99	99.99	0.002	99.99	99.99	0.009
Ventricular complex	6252	6246	3	3	99.95	99.81	0.0004	99.95	99.90	0.096

Of the total 149,718 normal complexes, the tested program identified 149,711. There were 10 missed complexes and 3 false positives. The evaluation parameters were as follows: sensitivity – 99.99%, specificity – 99.99%, false positive rate – 0.002%, positive predictive value – 99.99%, accuracy – 99.99%. The error was 0.009%.

Of the total 6,252 ventricular complexes, the program identified 6,246. There were 3 missed complexes and 3 false positives. The evaluation parameters were as follows: sensitivity – 99.80%, specificity – 99.80%, false positive rate – 0.001%, positive predictive value – 99.90%, accuracy – 99.71%. The error was 0.096%.

The resulting algorithm processes 40-minute records in 4.7 seconds, and a 24-hour record in about 3 minutes.

The standard ECG database of ROHMINE 2018 was used to test the PCard program under a standard mode. The test results are given in Table 2. Serious violations are noted in the Cito column.

Table 2

Final test results under a standard mode

Code	Conclusion	Cito	Doctors	Program	Missed	Falsely set	Sen, %	Ppn, %	Ppv, %
Rhythm									
1	Sinus rhythm	–	1500	1496	3	0	99.80	100	100
2	Tachycardia	–	130	130	1	1	99.24	99.30	99,24
3	Bradycardia	–	221	218	3	0	98.64	100	100
4	Fibrillation, atrial flutter	+	113	115	0	2	100	99.93	98,29
5	Atrial rhythm	–	13	12	1	0	92.30	100	100
6	AV rhythm, episode of AV rhythm	+	7	7	0	0	100	100	100
7	HT, episode of HT or rhythm	+	9	9	0	0	100	100	100
8	VT, episode of HT or rhythm	+	5	5	0	0	100	100	100
Extrasystole									
9	Supraventricular extrasystole	–	94	95	1	2	98.96	99.87	97,93
10	Ventricular extrasystole, parasystole	–	73	72	1	0	98.63	100	100
Pauses in AV conduction									
11	1st degree AV block	–	57	55	4	2	93.22	99.83	96,49
12	Short PQ syndrome	–	35	37	0	2	100	99.87	94,87
13	2nd degree AV block	+	15	15	0	0	100	100	100
14	Pause due to SA block or residual sinus node	+	9	11	1	3	91.67	99.81	78,57
15	Blocked supraventricular extrasystole	–	6	7	0	1	100	99.90	87,50
16	Pause longer than 2 sec against the background of AF or AT	+	9	9	0	0	100	100	100
20	3rd degree AV block	+	4	4	0	0	100	100	100
Ventricular conduction									
17	VPV, incl. transient	–	29	28	2	1	93.33	99.87	96,55
18	Complete BPN, incl. transient	–	45	46	0	1	100	99.90	97,87
19	Complete BLN, incl. transient	+	46	46	0	0	100	100	100
20	Complete BPVLN	–	17	17	0	0	100	100	100
QT									
21	QT prolongation	–	49	51	1	3	98.07	99.80	94,44
22	QT shortening	–	34	34	2	2	94.44	99.82	94,44
Coronary artery disease (CAD), Left Ventricular Hypertrophy (LVH)									
23	ACS with ST elevation or depression	+	16	15	1	0	93.75	100	100
24	MI with Q and non-Q, any stage	+	135	135	1	1	99.26	99.93	99,26
25	LVH	–	158	160	0	2	100	99.87	98,76
Total for the database									
For all violations (except syn.rhythm)		–	1329	1333	19	23	98.60	99.91	98.30
For violations Cito		–	368	371	3	6	95.37	99.97	98.40
Accuracy by base: 98.43%									

According to the data in Table 2, 1496 of the total sinus rhythms were detected, 3 of them were missed, the sensitivity was 99.80%, specificity was 100%, and the positive predictive value was 100%. For all disorders (except sinus rhythm), 1333 of 1329 disorders were detected, 19 of which were missed, and 23 disorders were detected incorrectly. The sensitivity in this case was 98.60%, specificity was 99.91%, and the positive predictive value was 98.30%. For serious disorders (Cito), 371 of 368 disorders were detected, 3 of which were missed, and 6 disorders were detected incorrectly. The sensitivity in this case was 95.37%, specificity was 99.97%, and the positive predictive value was 98.40%. The accuracy of the algorithm for the entire database was 98.43%. A comparative analysis of the results is illustrated in Table 3. For the developed modified algorithm based on the Pan-Tompkins method, the indicators were calculated as the arithmetic mean value according to the data in Table 1.

Table 3

Comparative analysis of algorithms

Method	Sens, %	Ppv, %
Developed algorithm	99.97	99.97
1st derivative method [24]	98.08	99.18
Hilbert transform [25]	99.88	99.73
Dynamic Bayesian network [26]	99.72	99.76
Differential threshold method [27]	99.69	99.63

Our results indicate the high accuracy of the proposed algorithm, which, in terms of the key metrics Sens and PPV, outperforms most of the known solutions reported in [24–27].

6. Discussion of results related to the automated diagnostics of electrocardiograms in real time based on the modified Pan-Tompkins algorithm

The proposed modified Pan-Tompkins algorithm for determining the boundaries of the QRS complex in the long-term monitoring system has made it possible to achieve high performance and quality indicators, ensuring the accuracy of the algorithm for determining normal complexes of 99.99%, for determining ventricular complexes – 99.90% (Table 1). When recording an ECG under the standard mode, the accuracy was 98.43%. Another equally important result of the presented modified algorithm is an increase in performance. During the research, it was found that approximately 4.7 seconds were spent on processing one record lasting 40 minutes, i.e., a 1-second segment of the signal is processed in approximately 1.97 ms.

The accuracy and speed of the algorithm were increased by modifying the Pan-Tompkins algorithm. Thus, at the first stage of signal processing, digital filtering based on wavelet transforms was used, which minimized the impact of interference of various natures. To increase the speed and accuracy of the algorithm, other mathematical operations, in contrast to the original algorithm, were used at the stage of calculating derivatives, and they were applied to all leads synchronously. At the integration stage, a recursive moving average filter was implemented, while the window width (w = 0.08 s) was selected empirically. Visual results obtained at the stage of calculating derivatives and moving average (Fig. 3) demonstrate high sensitivity of the algorithm to QRS complexes. Also, at the final stage of the algorithm, methods for determining the boundaries of QRS complexes and RR intervals were used that differ from the original. They make it possible to analyze the rhythm and examine its disturbances, as well as determine the rise and fall of the ST segment, which are the main goals of ECG monitoring. The consistency of boundary detection for all leads (Fig. 4) confirms the correctness of the algorithm for multichannel signal processing and its suitability for use in 12-channel systems.

In [28], a modified Pan-Tompkins algorithm was proposed for real-time QRS detection on mobile platforms (AMRT). It turned out to be more correct than the original algorithm. To test the algorithms, the author used the PhysioBank ATM and Harvard Dataverse databases for the following ECS categories: high (A1) and low signal quality (A2), normal sinus rhythms (B1), arrhythmias (B2), a subset of the arrhythmia data set (C), and signals obtained using telemedicine (D). The following accuracy was obtained for the Pan-Tompkins algorithm: A1 – 99.26%; A2 – 74.09%; B1 – 94.85%, B2 – 96.09, C – 64.26 and D – 68.91. For the AMRT algorithm: A1 – 99.62%; A2 – 78.54%; B1 – 94.96%, B2 – 96.66, C – 92.81, and D – 76.29.

Analyzing our results, it can be noted that the accuracy of the proposed algorithm is higher than the original, but there is a fairly large difference between the categories. Thus, it can be concluded that the stability of solutions to changes in influencing factors is not at a high level. The results can be compared with the results of the algorithm developed in the paper for categories B1, B2, and C, using the data in Table 2. The accuracy across the entire database was 98.43%, which exceeds the accuracy of the AMRT algorithm.

It should be noted that when using the original Pan-Tompkins algorithm, the calculation time for a 1-second signal segment is approximately 20 ms. Therefore, a 40-minute recording will take approximately 48 seconds. For the differential threshold method [27], the calculation time for a 1-second signal segment is approximately 10 ms, and for a 40-minute recording – 24 seconds. The algorithm reported in our study is 10 times faster than the Pan-Tompkins algorithm and 5 times faster than the method based on the dynamic Bayesian network [26].

At the same time, the differential threshold method [27] requires approximately 2 seconds to record a 40-minute recording, which is 2.4 times less than the processing time of the proposed algorithm. However, if one looks at the indicators in Table 3, the differential threshold method is inferior in signal processing quality. Here, it is important to maintain a reasonable balance between processing quality and time spent, giving preference to quality, since this subsequently affects the accuracy of the diagnostic conclusion.

The described PCard program, developed on the basis of the proposed algorithm, makes it possible to record and automatically process ECG in 12 standard leads, both during long-term monitoring and under the standard mode. The program implements the entire cycle of automated ECG analysis, from registration to the formation of a diagnostic report (Fig. 5). A special feature of the

program is the ability to use it for mobile wireless systems that involve long-term monitoring in real time. As a rule, the functionality of such programs is limited by the number of analyzed leads, the lack of the ability to conduct a medical analysis to confirm the results [6, 29], an abbreviated diagnostic report (only for arrhythmias or ischemic disorders). Also, not all programs include a user-friendly interface and such a large set of diagnostic criteria (300 criteria) as in the PCard software.

It should be noted that despite the high accuracy of the automatic analysis and the ability to obtain a diagnostic report (Fig. 8), our program should serve as an auxiliary tool for accelerating and increasing the accuracy of ECG interpretation. The software does not replace professional medical judgment, so the final conclusion must be given by a qualified physician, for which purpose the "Borders" mode is provided (Fig. 9).

This study has the following limitations: maximum heart rate (HR) is 240 beats per minute; minimum HR is 30 beats per minute. The sampling frequency of samples is no more than 1000 Hz, the data are processed as 12-bit ECS values (resolution), which basically corresponds to a large-scale ECG. Diagnostics is limited in the case of only individual leads, i.e., when one or two leads are used.

Disadvantages include the fact that in the case of noisy ECG signals (interference, surges, floating isoline, etc.), the stability of the algorithm is significantly reduced. Given this, corrective actions are required.

Future research to build on our study may involve application of the results to design a prototype of a mobile device aimed at long-term monitoring with the possibility of wireless Wi-Fi transmission of ECG in real time. From a practical point of view, the implementation of the proposed modified Pan-Tompkins algorithm as part of the PCard module in the C++ language allows for further adaptation to various operating systems and hardware platforms of mobile diagnostic devices. However, successful implementation of the algorithm in medical devices will be possible only with a comprehensive approach, including both technical modification to meet the needs of patients and medical personnel, and integration with modern standards of mobile medical diagnostics.

7. Conclusions

1. The result of our study is the improved key stages of the original Pan–Tompkins algorithm that previously limited diagnostic quality and increased data processing time. The modifications affected the stages of digital filtering, numerical differentiation, integration, and adaptive threshold analysis. Taking into account synchronous signals from several leads and compression of calculations made it possible to increase the accuracy of determining the coordinates of R waves and QRS complex boundaries while maintaining high computational efficiency. The results of the Pan-Tompkins algorithm improvement made it possible to ensure reliable extraction of key ECG elements even under conditions of noise and limited resources, which confirms its applicability in mobile and wearable diagnostic devices. Its speed and accuracy will allow its application in online analysis of cardiological data. In addition, it does not require large hardware and system resources, which makes it convenient for use in mobile devices with autonomous power supply.

2. The implemented PCard software integrates the developed modified algorithm for determining the boundaries of the QRS complex and is intended for use in a hardware-software system for long-term and standard ECG monitoring in 12 leads. Testing of the PCard program, which operates on the basis of the developed algorithm, was carried out under the Holter monitoring mode and under a standard mode. The test results showed a fairly high accuracy for various types of pathologies. For Holter monitoring, the accuracy in determining normal complexes was 99.99%, and in determining ventricular complexes – 99.90%. The resulting algorithm processes records lasting 40 minutes in 4.7 seconds, and a record lasting 24 hours in 3 minutes. The accuracy of the algorithm under a standard mode for the entire database of pathological disorders was 98.43%. The PCard program makes it possible to automatically receive up to 300 diagnostic criteria and diagnostic conclusions that can be adjusted by a doctor before printing. The software also allows for digital filtering of ECS, eliminating interference, and thus increasing the accuracy of diagnostics. In addition, the program provides the ability to work with archived records made on other devices. Also, one of the advantages of the software is the ability to simultaneously conduct long-term monitoring and online analysis of ECG, which will make it possible to identify pathological disorders in real time.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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