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CARDIAC SIGNAL PROCESSING WITH ALGORITHMS USING VARIABLE RESOLUTION

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ABSTRACT

Context. The proposed paper relates to the field of cardiac signal processing, in particular, to the segmentation of the cardiac signal into cardiac cycles, as well as one of the most important features definition used in cardiac diagnosis, the *T*-wave end.

Objective. The purpose and object of study is to develop an algorithm for processing the cardiac signal in the presence of interference that allows the identification of features necessary for diagnosis and, at the same time, does not distort the original signal as is usually the case when it is processed by band-pass digital filters to exclude interference, which leads to the original signal distortion and, possibly, loss of diagnostic features.

The proposed **Method** involves representing the cardiac signal as part of some image contour. Cardiac signal processing consists first of all in segmentation into cardiac cycles. Usually, *R*-waves are used to segment the cardiac signal into cardiac cycles, i.e., the sequence of *R*-waves in the processed part of the cardiac signal is determined. When determining the *R*-wave, a model is used that assumes an increase in the signal followed by a decrease, and the increase (decrease) rate must be greater in absolute value than a certain predetermined value. For a selected segment of the cardiac signal, the sequence of *R*-waves is determined at different resolutions. The answer is the sequence that is repeated for the largest number of resolutions and that is used to segment the cardiac signal into cardiac cycles. The *T*-wave model can be represented as a sequence of curved arcs without breaks. In one of the common cases, the *T*-wave is determined by the largest maximum of the cardiac signal within the cardiac cycle, following the R-wave. The end of the *T*-wave is determined by the first minimum following the already determined maximum for the *T*-wave. As in the case of cardiac signal segmentation, the maximum of the *T*-wave and the *T*-wave end are determined at different resolutions, and the answer is considered to be those values that coincide at the largest number of used resolutions.

Results. Algorithms for cardiac signal processing using variable resolution have been developed and experimentally verified, namely, the algorithm for segmentation of the cardiac signal into cardiac cycles and the algorithm for *T*-wave end detection, which is of great importance in cardiac diagnostics. Means of cardiac signal processing, using the proposed algorithms, do not change the processed cardiac signal, unlike traditional means that use filtering of the cardiac signal, distorting the cardiac signal itself, which leads to distortion of the processing result.

Conclusions. Scientific novelty consists in the fact that algorithms of cardiac signal processing in the presence of interference using variable resolution typical of visual perception are proposed.

The practical significance consists in the fact that the means of cardiac signal processing, using the proposed algorithms, do not change the processed cardiac signal, unlike traditional means that use filtering of the cardiac signal, distorting the cardiac signal itself, which leads to distortion of the processing result. The use of the presented tools in practical medical practice will lead to an improvement in the quality of cardiac diagnostics and, as a result, the quality of treatment.

KEYWORDS: cardiac signal, segmentation, cardiac cycles, *T*-wave end, variable resolution.

ABBREVIATIONS

ECG is an electrocardiogram.

NOMENCLATURE

P-wave is an electrocardiogram element;
Q-wave is an electrocardiogram element;
R-wave is an electrocardiogram element;
S-wave is an electrocardiogram element;
T-wave is an electrocardiogram element;
ST-segment is an electrocardiogram element;
QRS is a complex of three waves – *Q*, *R*, *S*;
Tpeak and Tend are some *T*-wave points;
(x_i, y_i) is a sample pair number i from a sequence that are discrete realization of the function $y(x)$, representing cardiosignal;
$x_1=a$, $x_I=b$, (a,b) is a domain of signal definition;
I is a number of samples in the domain definition;
$\{R(e)\}$ is a final list of *R*-waves;
q is a number samples in the "coarse" sample, which determine the current resolution;
J is a number of "coarse" samples at a given resolution m;
z_j is a value of the "coarse" count j ;
w_j is a sample sequence of the "coarse" count j, at a given resolution m;
m is an one of the the current resolutions;
$Z^{(m)} = \{z_j^{(m)}\}$ is a discrete realization of the function $y(x)$ at a resolution m;
$i_Q^{(j)}$ is a sample number of the sequence I, corresponding to the "coarse" sample j at a resolution m, which represent *Q*-wave;
$i_R^{(j)}$ is a sample number of the sequence I, corresponding to the "coarse" sample j at a resolution m, which represent *R*-wave;

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$i_S^{(j)}$ is a sample number of the sequence I, corresponding to the "coarse" sample j at a resolution m, which represent S-wave;

Q is a value of Q-wave at sample $i_Q^{(j)}$;

R is a value of R-wave at sample $i_R^{(j)}$;

Q is a value of Q-wave at sample $i_S^{(j)}$;

θ is a predetermined threshold to recognize R-wave;

$R^{(m)} = i_{R_1}^{(m)}, i_{R_2}^{(m)}, ..., i_{R_n}^{(m)}, ...$ is a preliminary answer for R-wave sequence samples at resolution m;

d is a predetermined threshold to recognize T-wave.

INTRODUCTION

The electrocardiogram (ECG) reflects the electrical activation of the heart and is an important biomedical signal for determining the functional state of the heart. The ECG consists of a repetitive sequence of P, QRS and T waves associated with each heartbeat (Fig. 1). The detection of QRS complexes in the cardiogram is used to break it down into a sequence of individual cardiac cycles, i.e., primary segmentation. After determining the location of QRS complexes in the cardiogram, this information can be used to construct ECG-derived signals, such as amplitude and rhythmograms, or to further find individual components of the cardiac cycle.

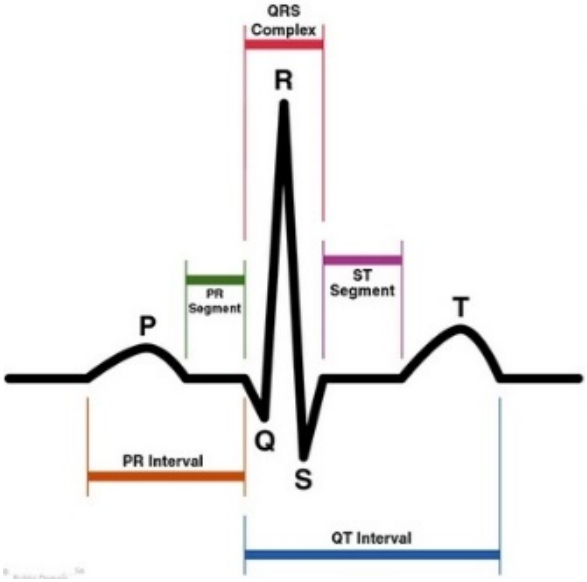

Figure 1 – Cardiac cycle graph image

Various features of the ECG signal are useful for diagnosing heart disease. Reliable detection of the P and T waves is more difficult than the QRS waves for several reasons, including their low amplitude, low signal-to-noise ratio, amplitude and morphological variability, and even possible overlap of the P-wave with the QRS complex. A flattened or negative T wave is interpreted as a symptom of coronary heart disease. P-wave prolongation can be used to detect atrial fibrillation.

Traditionally, the electrocardiac signal is filtered to exclude interference. Since the frequency parameters of interference cannot be determined, filtering often leads to distortion of the electrocardiogram and, consequently, to a decrease in the quality of diagnostics.

The human visual system processes the visual image of a cardiac signal almost instantaneously, even in the presence of interference.

The implementation of variable resolution means processing an image, in particular an electrocardiac signal, using a certain number of resolutions. This paper deals with the development of algorithms for segmentation and detection of cardiac signal elements using variable resolution.

The subject of study is the processing of electrocardiograms as a special case of an image. The proposed method uses a variable resolution, which should provide satisfactory results in the presence of interference, without the use of pre-filtering the electrocardiogram signal. Pre-filtering with predefined and specified filter parameters is typical for most electrocardiogram processing methods, which significantly limits the application in the presence of interference.

The purpose of the work is to develop an algorithm for processing an electrocardiogram as a special case of an image, in particular, to determine the end of the T wave, which is an important diagnostic factor. Variable resolution should be used in the development of the algorithm to ensure satisfactory performance in the presence of interference without using filtering of the electrocardiogram signal with predefined and specified filter parameters.

1 PROBLEM STATEMENT

Let the sequence of measurements of the cardiac signal be given as $(x_i, y_i), i = \overline{1,I}$; $x_1=a$, $x_I=b$, where (a,b) is the signal detection domain, I is the number of measurements in the detection domain.

The first task is to segment the cardiac signal into cardiac cycles by determining the sequence of R-waves $\{R(e)\}$, $(e=1,...,E)$, where E is the number of R-waves.

The main task is to determine for each cardiac cycle in the $(R(e), R(e+1))$, $(e=1,...,E-1)$ interval the number of the count corresponding to the end of the T-wave, that is, the minimum signal value immediately following the maximum signal value for the T-wave.

Commonly used approaches to cardiac signal segmentation, T-wave recognition, and T-wave endpoint detection involve the use of bandpass filters to eliminate interference. There is an empirical understanding that useful ECG signals belong to the frequency range of 0.5 Hz – 10 Hz. All frequencies outside of this range are considered interference. However, it is possible that the interference appears in the same frequency range as the useful ECG signal, as well as for certain parts of the ECG signal, frequencies greater than 10 Hz are specific. As a result, the processed signal may be distorted. In this case, either the ECG signal processing may be refused, or errors in

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cardiac signal processing are possible, and, as a result, it is impossible to provide the patient with a high-quality ECG diagnosis.

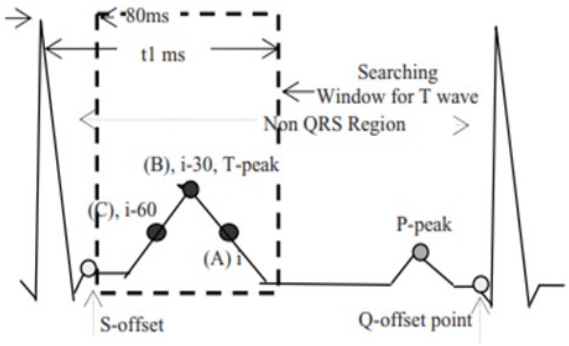
It is relevant to develop methods and algorithms that are capable of processing an ECG signal in the presence of interference without the use of bandpass filters. In particular, methods and algorithms that use variable resolution do not affect the signal at all, and the cardiac signal to be processed.

This paper presents an algorithm for segmenting the cardiac signal, recognizing *T*-waves and *T*-wave endpoints with variable resolution.

2 REVIEW OF THE LITERATURE

Various methods for detecting *T*- and *P*-waves can be found in the literature: Discrete Fourier Transform, Discrete Cosine Transform, and adaptive filters. The distinction between *P*- and *T*-waves is considered in [1–3]. An algorithm based on fractional-order digital differentiation for detecting *P*- and *T*-waves is proposed [4]. A method for detecting monophasic *P*- and *T*-waves is described in [5]. A generalized and robust method for *P*-and *T*-waves detection is described in [6]. The identification of *P*-and *T*-waves based on fuzzy theory is discussed in [7]. A multi-stage methodology using wavelet transform is used to determine the *P*-waves, as proposed in [8]. The Discrete Wavelet Transform, which uses the Haar wavelet to detect the peak of the *T*-waves and the end of the *T*-wave, is considered in [9]. A mathematical model based on *T*-waves recognition is proposed in [10]. The classification and identification of *T* and *P* waves based on the support vector method is discussed in [11]. In recent years, there has been a significant use of systems based on field programmable gate arrays for ECG processing [12] and *QRS* detection [13].

In [14, 15], the algorithm for detecting *P* and *T* waves implemented in real time is considered. The *P* and *T* waves are identified based on their location in the non-*QRS* region and the corresponding *T* and *P* waves search zones are formed. The waves detection algorithm is divided into two parts, namely, the training period and the detection period. During the initial training period, the characteristic of the *R*-wave, the *R–R* interval, the polarity and the maximum slope of the *T* and *P* waves are determined (Fig. 2). If *i* (point A) is the current reading, then points B and C correspond to the *i*-30 and *i*-60 positions of the readings In Fig. 2 shows the probable positions A, B, and C located in the *T*-wave. The point B, which corresponds to the (*i*-30th) count, is checked for the presence of a valid *T* or *P* peak after the *i*-th count. The slopes of segments BA and BC relative to point B must correspond to certain predefined values.



[t1= last detected R-peak index + half of average R-R interval -10]

Figure 2 – *T*-peak detection

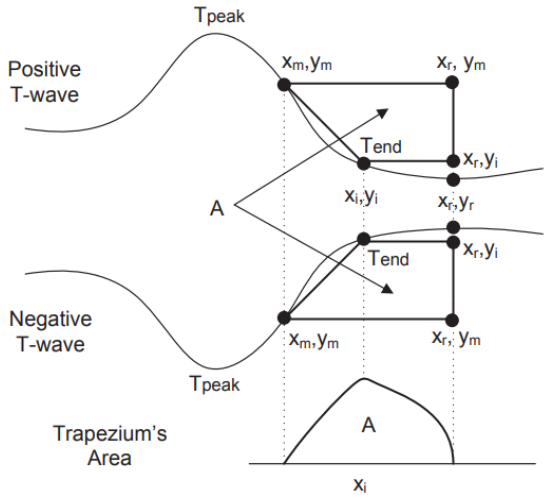


Figure 3 – Determination of the *T*- wave end (for a monophasic wave) by calculating the areas of several trapezoids formed by three fixed points and one moving point (x_i, y_i). The trend corresponds to the point where the area A is maximized

Paper [16] presents a robust and numerically efficient method based on two moving average filters developed to detect P and T waves in electrocardiograms (ECGs). The algorithm that implements the method detects *P*-and *T*-waves in the presence of interference.

It uses preliminary information about the duration of the *P*-and *T*-waves to make decisions. Bandpass filtering is applied to eliminate baseline drift and high frequencies.

Detection of *T*-wave endpoints on an ECG is a basic procedure for ECG processing and analysis[17,18].

In [19], an algorithm for detecting the end point of the *T*-wave on the ECG in the presence of broadband noise was investigated.

To detect the *Tend* point, various methods have been proposed based on: line intersection [20], thresholding by *T*-wave amplitude [21], thresholding by the first derivative of the ECG signal [22], calculating distances [23], angles [24], and areas [25], correlation with a pattern [26], mathematical models of the ECG [27], wavelet transform [28], and other methods. All of them have certain advantages and disadvantages due to complexity, computational costs, morphological variations of

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waveforms, sensitivity to noise, and dependence of *Tend* on the threshold.

The trapezoidal area method assumes that *T*-peaks are found by searching for maxima and local minima in a window that starts with the previous *R*-wave peak.

The trapezoidal area method method is based on the calculation of successive areas of a rectangular trapezoid with three fixed vertices and one moving vertex: (x_i, y_i), which is shifted under the influence of the signal from point (x_m, y_m) to point (x_r, y_i), and the total area is calculated. The *T*-wave is defined as the point where the area A of the trapezoid is maximized (Fig. 3).

3 MATERIALS AND METHODS

In terms of image processing within the structural model, the part of the cardiac signal to be processed is part of a contour that delimits some imaginary object. Like any contour, the cardiac signal can be described as a cellular complex with a sequence of 1-cells and 0-cells [29]. Cardiac signal processing consists primarily in segmentation into cardiac cycles. Usually, *R*-waves are used to segment the cardiac signal into cardiac cycles, i.e., the sequence of *R*-waves in the processed part of the cardiac signal is determined. An *R*-wave can be represented by a model (Fig. 4), which is determined by two events: a rise along the *QR* line and a fall along the *RS* line. The derivative of the rise and fall must be greater than a certain value of θ in absolute value.

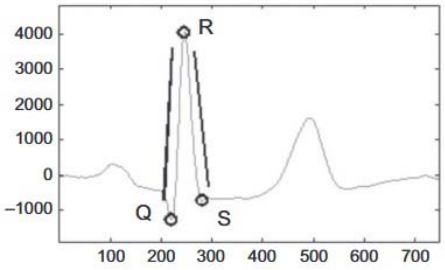

Figure 4 – The *R*- wave as a sequence of two events: 1) growth along the QR line; 2) decline along the RS line.
The derivative of growth and decline in absolute value must be greater than a certain value of θ

Further processing of the cardiac signal is performed within cardiac cycles. A cardiac cycle is a part of the cardiac signal between two adjacent *R*-waves. In particular, the *T*-wave is a part of the cardiac cycle located next to the *QRS* complex or next to the *ST*-segment, which is not always present in the cardiac signal. The most accurate determination of the *T*-wave end is considered particularly important for diagnosis. The *T*-wave can be monophasic – one wave is positive or negative, or biphasic (positive-negative, or vice versa). In this study, we consider the monophasic positive case. It is believed that other configurations can be considered as variants of this basic case. The complexity of determining the *T*-wave end increases due to the presence of interference.

It should be noted that the *T*-wave as a detection object has certain differences from other cardiac signal objects, in particular, from the *R*-wave. Usually, contour objects that are sequences of line segments and curve arcs have breakpoints in their composition, for example, like an *R*-wave. A *T*-wave, on the other hand, usually does not contain any breakpoints. Therefore, a *T*-wave is an object without any specific points, in particular, without clearly defined start and end points. Since we are considering the monophasic positive case, the *T*-wave is defined by the following two events:

1. the presence of the first signal maximum after the *R*-wave and

2. a minimum or a certain interval following it, the signal level of which is close to the baseline level.

Determination of *R*-wave and *T*-wave features is complicated by the presence of interference. In the presence of interference, the events that define the elements of the cardiac signal are determined using variable resolution [30].

Thus, the detection of both *R*-waves and *T*-waves is conditioned by the determination of two events characteristic for each of them.

The proposed algorithm defines a separate event for the discrete realization of the ECG signal at variable resolution. That is, two types of events should be defined – rise and fall – to determine the *R*-wave, and two types of events – maximum and minimum – to determine the *T*-wave. All types of events must be determined by the proposed algorithm.

A discrete realization is a sequence of measurement pairs $(x_i, y_i), i = \overline{1,I}$; $x_1=a$, $x_I=b$, where (a,b) is the signal detection domain, I is the number of measurements in the detection domain.

The definition area is divided into equal intervals, the values of which are set and changed during the operation of the algorithm. Each interval contains the same number of samples q, which determines the resolution The number J of parts, containing q samples, corresponding to the function definition domain determines the number of "coarse" samples at a given resolution. For each of the parts $q_j, j = \overline{1,J}$, the value of the "coarse" counts $z_j = g(w_j)$ is calculated from the sequence of counts $w_j = \{y_{q*(j-1)+1}, y_{q*(j-1)+2}, \ldots, y_{q*(j-1)+q}$, that are part of this interval. All values of the coarse samples form a discrete realization of the function $Z^{(m)} = \{z_j^{(m)}\}, j = \overline{1.J}$ at a given resolution m, where $m = \overline{1,M}$, is the total number of resolutions used to solve the problem using this algorithm.

An *R*-wave is characterized by two events. Event (R1) is an increase in the signal from the value of Q corresponding to the sample $i_Q^{(j)}$ to the value of R corresponding to the sample $i_R^{(j)}$. Event (R2) is a decrease in the signal from the value of R corresponding to the sample

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$i_R^{(j)}$ to the value of S corresponding to the sample $i_S^{(j)}$. The value of growth and decline (first derivative) by absolute value must exceed a predetermined threshold $(R-Q)/(i_R^{(j)}-i_Q^{(j)})>\theta$, and $(R-S)/(i_R^{(j)}-i_S^{(j)})>\theta$.

The list of sample numbers for *R*-waves that form a preliminary answer for resolution *m*: $R^{(m)}=iR_1^{(m)}, iR_2^{(m)},..., iR_n^{(m)},...$ Two preliminary answers for resolutions *m* and *m* + 1 are the same if:

1. The number of *R*-waves for $R^{(m)}$ is equal to the number of *R*-waves for $R^{(m+1)}$, i.e. the lengths of the both lists are equal.

2. The condition $(i\,R_n^{(m)}-q^{(m)})\le i\,R_n^{(m+1)}\le(i\,R_n^{(m)}+q^{(m)})$ is fulfilled. That is, the count number of the R_n-wave from the list $R^{(m+1)}$ corresponds to the count number of the R_n-wave from the list $R^{(m)}$, if the count number $i\,R^{(m+1)}$ of the *R*-wave does not differ from the count number $i\,R^{(m)}$ of the *R*- wave by more than $q^{(m)}$.

The allocation of the *T*-wave end immediately following the *QRS* complex is considered on the case of a positive monophasic *T*-wave. It should be noted that the maximum value of the *T*-wave is the largest after the *R*-wave, and the end of the *T*-wave is determined by the beginning of the minimum value following the maximum of the *T*-wave.

The *T*-wave is the part of the cardiac cycle following the *ST*-segment and is characterized, in particular, by two events. The event (T_1) is defined as the determination of the maximum signal value in the definition area. Event (T_1) is characterized by the corresponding "exact" count $i^{(j)}=j*q$ and the bounds of the cardiac cycle at which the event was recorded. The event (T2) is defined as the determination of the minimum signal value within the current cardiac cycle or one that does not exceed a predetermined threshold *d*, with $i_{(T2)}>> i_{(T1)}$, i.e., the event (T_2) occurs significantly after the event (T_1).

Next, we present an algorithm for segmenting the ECG into cardiac cycles and an algorithm for determining the *T*-wave endpoints for discrete realization of the ECG signal at variable resolution.

The main steps of the algorithm are:

1. Determine the number of "coarse" samples *J*, the number of resolutions *M*, and the values of the variables at the initial resolution *m*=1.

2. For each value of the resolution *m* (*m*=1,...,*M*), the lists of events {$R_1(m)$}, {$R_2(m)$} are formed, which determine the list of *R*-waves – {*R*(*m*)}, more precisely the list of their sample numbers $\{i_{R^{(m)}}\}$.

3. Determine the lists of *R*-waves – {*R*(*m*)}, which are appropriate, that is, the same for the largest number of resolutions, which form the answer to the final list of *R*-wave samples – {*R*(*e*)}, (*e*=1,...,*E*), more precisely the list of their sample numbers $\{i_{R^{(e)}}\}$, where *e* is the number of *R*-waves in the final list.

4. For each of the cardiac cycles having an interval $(i\,R^{(e)}, i\,R^{(e+1)})$, (*e*=1,...,*E*–1), the maximum signal value located in the sequence of samples after the *QRS* complex at all resolution values is determined. These values are preliminary answers to the maximum value of the *T* wave.

5. For each of the cardiac cycles having an interval $(i\,R^{(e)}, i\,R^{(e+1)})$, (*e*=1,...,*E*–1), determine the minimum signal value (or one that is close to the baseline) located in the sequence of samples after the maximum value determined in the previous step at all resolution values. These values are preliminary answers to the end of the *T* wave.

6. For each of the cardiac cycles, among the preliminary responses to the maximum value and the end of the *T*-wave, determine those that are appropriate, that is, the same for the greatest number of resolutions. The obtained values of the *T*-wave ends are considered final and a list of *T*-wave end values is formed.

4 EXPERIMENTS

In the process of experimental verification of the proposed algorithm using variable resolution, more than 100 fragments of cardiograms were processed, each containing about 30 cardiac cycles. Although the selected fragments of cardiograms were distorted by noise, no preprocessing of the cardiac signal, in particular, filtering, was used. Cardiograms with monophasic *T*-waves were selected for the experiment, which does not affect the generalizability of the results to other types of *T*-waves. An example of cardiac signal fragment segmentation in the presence of interference is shown in Fig. 5. Fig. 6 shows examples the *T*-waves endpoint determining.

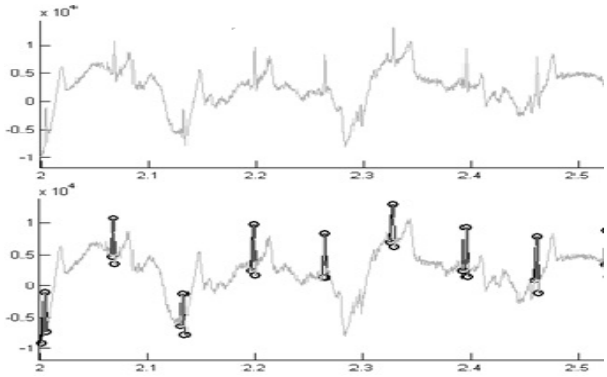

Figure 5 – An example of cardiac signal fragment segmentation in the presence of interference

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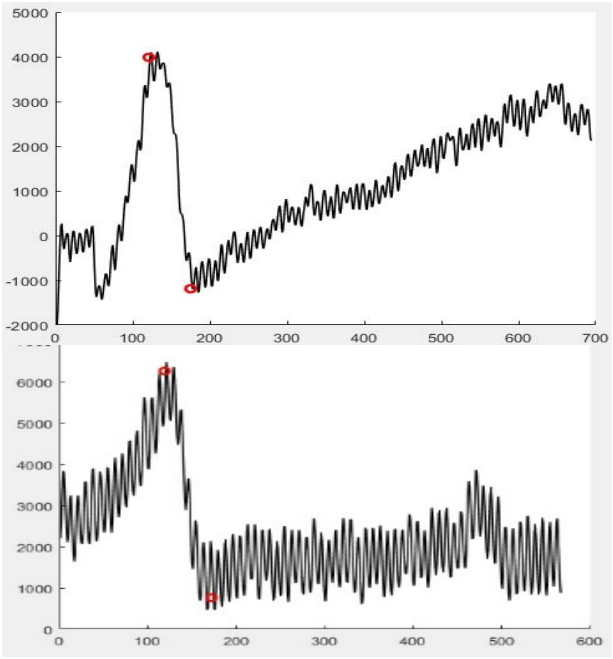

Figure 6 – Examples the *T*-waves endpoint determining

5 RESULTS

Algorithms for cardiac signal processing using variable resolution have been developed and experimentally verified, namely, the algorithm for segmentation of the cardiac signal into cardiac cycles and the algorithm for *T*-wave end detection, which is of great importance in cardiac diagnostics.

Means of cardiac signal processing, using the proposed algorithms, do not change the processed cardiac signal, unlike traditional means that use filtering of the cardiac signal, distorting the cardiac signal itself, which leads to distortion of the processing result.

6 DISCUSSION

ECG is most often distorted by noise in the measurement process and analog-to-digital conversion. The predominant noise in ECG is baseline wander, power line noise and electromyogram. Baseline wander is caused by the patient's movements due to breathing; the frequency range of baseline wander is usually below 0.5 Hz, which is in the same frequency range of ST segments. Power line noise is the 50 Hz/60 Hz component caused by parasitic electromagnetic fields from power lines and interferes with the analysis of low-amplitude components. It is necessary to place power lines as far away as possible or shield them, since improper electrical insulation will cause such noise. Electromyogram is a signal caused by muscle activity in the body, its frequency band is in the range of (5 Hz – 2 kHz) or (1 Hz – 5 kHz), its influence is difficult to exclude because its frequency band overlaps with the frequency band of ECG. In addition, there are other sources of interference due to motion artifacts, electrode contacts and electronic devices.

There are 4 typical filter processes in an ECG device: (a) anti-aliasing and upper-frequency cutoff, (b) baseline wander suppression and lower-frequency cutoff, (c) line-frequency rejection, and (d) muscle artifact reduction.

All types of frequency filtering affect the original cardiac signal to one degree or another, which leads to its distortion and loss of diagnostic features. At the same time, when processing the cardiac signal by algorithms using variable resolution, the original cardiac signal does not change in principle, all diagnostic features are preserved, can be identified and used.

Algorithms for cardiac signal processing using variable resolution have been developed and experimentally verified, namely, the algorithm for segmentation of the cardiac signal into cardiac cycles and the algorithm for *T*-wave detection, which is of great importance in cardiac diagnostics. The probability of a correct answer for traditional algorithms using pre-filtering is up to 98%. No errors were found in the experimental validation of the proposed algorithms. This makes it possible to eliminate distortion of the cardiac signal during ECG acquisition and improve the quality of cardiac diagnostics.

CONCLUSIONS

The article deals with algorithms of cardiac signal processing.

Scientific novelty consists in the fact that algorithms of cardiac signal processing in the presence of interference using variable resolution typical of visual perception are proposed.

The practical significance consists in the fact that the means of cardiac signal processing, using the proposed algorithms, do not change the processed cardiac signal, unlike traditional means that use filtering of the cardiac signal, distorting the cardiac signal itself, which leads to distortion of the processing result. The use of the presented tools in practical medical practice will lead to an improvement in the quality of cardiac diagnostics and, as a result, the quality of treatment.

Prospects for further research are as follows. It is supposed to develop tools for selecting all objects of the cardiac cycle.

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ОБРОБЛЕННЯ КАРДІОСИГНАЛУ АЛГОРИТМАМИ, ЩО ВИКОРИСТОВУЮТЬ ЗМІННУ РОЗДІЛЬНУ ЗДАТНІСТЬ

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АНОТАЦІЯ

Актуальність. Запропонована робота відноситься до області обробки кардіосигналів, зокрема, до сегментації кардіосигналу на серцеві цикли, а також до визначення однієї з найважливіших ознак, що використовується в кардіодіагностиці, – кінця зубця *T*.

Мета. Метою і завданням дослідження є розробка алгоритму обробки кардіосигналу в присутності завад, який дозволяє виділити необхідні для діагностики ознаки і, в той же час, не спотворює вихідний сигнал, як це зазвичай відбувається при його обробці смуговими цифровими фільтрами для виключення завад, що призводить до спотворення і можливої втрати діагностичних ознак.

Запропонований **метод** полягає у представленні серцевого сигналу як частини контуру певного уявного зображення. Обробка серцевого сигналу полягає перш за все у сегментації на серцеві цикли. Зазвичай *R*-зубці використовують для сегментації серцевого сигналу на серцеві цикли, тобто визначають послідовність *R*-зубців в частині серцевого сигналу, що підлягає обробленню. При визначенні *R*-зубця використовується модель, яка передбачає збільшення сигналу з наступним його зменшенням, причому швидкість збільшення (зменшення) має бути за абсолютною величиною більшою, ніж певне задане значення. Для обраного сегмента серцевого сигналу послідовність *R*-зубців визначається з різними роздільними здатностями. Відповіддю є послідовність, яка повторюється для найбільшої кількості роздільних здатностей з тих, що були задіяні для сегментації серцевого сигналу на серцеві цикли. Модель *T*-зубця можна представити як послідовність дуг кривих без розривів. В одному з поширених випадків *T*-зубець визначається найбільшим максимумом серцевого сигналу в межах серцевого циклу, наступним за *R*-зубцем. Кінець *T*-зубця визначається першим мінімумом, наступним за вже визначеним максимумом для *T*-зубця. Як і у випадку сегментації серцевого сигналу, максимум *T*-зубця і кінець *T*-зубця визначаються при різних роздільних здатностях, а відповіддю вважаються ті значення, які збігаються при найбільшій кількості роздільних здатностей з тих, що були використані.

Результати. Розроблено та експериментально перевірено алгоритми оброблення кардіосигналу, що використовують змінну роздільну здатність, а саме алгоритм сегментації серцевого сигналу на кардіоцикли та алгоритм виявлення кінця зубця T, що має велике значення в кардіологічній діагностиці. Засоби оброблення серцевого сигналу, що використовують запропоновані алгоритми, не змінюють оброблений кардіосигнал, на відміну від традиційних засобів, які використовують фільтрацію серцевого сигналу, спотворюючи сам серцевий сигнал, що призводить до спотворення результату оброблення.

Висновки. Наукова новизна полягає в тому, що запропоновано алгоритми обробки серцевого сигналу за наявності перешкод із використанням змінної роздільної здатності, характерної для зорового сприйняття. Практичне значення полягає в тому, що засоби оброблення кардіосигналу, які використовують запропоновані алгоритми, не спотворюють кардіосигнал, що оброблюється, на відміну від традиційних засобів, які використовують фільтрацію серцевого сигналу, що призводить до спотворення результату оброблення. Використання представленого інструментарію в практичній медичній практиці призведе до підвищення якості кардіологічної діагностики і, як наслідок, якості лікування.

КЛЮЧОВІ СЛОВА: кардіосигнал, сегментація, кардіоцикли, кінець зубця *T*, змінна роздільна здатність.

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