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WAVELET-BISPECTRUM METHOD FOR DETERMINING QRS COMPLEX POSITIONS IN ECG SIGNALS

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Abstract. *The paper considers and investigates a new method for determining the positions of characteristic points of an electrocardiographic signal based on wavelet-bispectrum signal processing, which provides an increase in the probability of determining the R-characteristic point by 7.24% in contrast to standard methods, achieving a probability of correct determination of 99.96%. The results of the study of the effectiveness of the proposed method are demonstrated using real signals taken from the open database "Computing in Cardiology Challenge 2013", as well as the MIT-BIH and QT-Database databases. The conducted studies demonstrate that the results obtained for the MIT-BIH database are better than the results of other authors, and the sensitivity of the proposed method reaches 99.96%, while for the QT-Database 100%, which indicates the high efficiency of this method. One of the main problems of the proposed approach is the dependence on the length of the initial signal. If the signal being processed has a high duration, then the wavelet-bispectrum calculations will be much slower, due to the dependence of the number of frequency samples on the signal length in the wavelet transform, on which the dimension of the bispectrum will also depend. The higher it is, the longer the calculations are performed. When implementing the proposed method, this feature was considered and corrected by segmenting the signal and processing local fragments. Also, for a better calculation, a comparison of signal fragments in the found positions of QRS complexes was added, after which a correlation analysis of the found fragments was performed, and fragments that have a correlation by modulus lower than 0.3 are removed and not considered as QRS complex positions. By using this application of procedures, the method becomes invariant to interference, can search for distorted, non-stationary QRS complexes, and allows processing of long-term records. This method, with additional modification, can also be used to find other characteristic points of the QRS complex: P, Q, S, T.*

Key words: *ECG signal, QRS complex, wavelet transform, Morlet wavelet, wavelet-bispectrum.*

Introduction.

Monitoring physiological parameters is extremely important for assessing a person's condition. One of the main physiological parameters is the human electrocardiogram (ECG). In addition, the ECG signal can be used to assess another important physiological parameter - blood pressure. Also, the ECG signal can be processed to determine the respiratory rate [1, 2]. It is also worth noting that the determination of heart rate using the ECG signal is based on measuring the temporal position of QRS complexes corresponding to the moments of heart contractions. The

QRS complex is used as a reference point for classifying the cardiac cycle and detecting any abnormalities [3, 4]. One of the problems in determining the positions of the QRS complex in ECG signals is the presence of a large number of noise components. For the most part, various methods of isolating the useful signal from the background of interference are used to determine the positions of the QRS complex, which begin with pre-processing of the signal based on linear filtering in a certain frequency band, which allows limiting part of the interference components [5]. However, the use of such filtering also affects the parameters of the studied signal and subsequently the efficiency of determining the positions of the QRS complex. The main problem is to determine the optimal frequency band for pre-filtering of ECG signals [6]. The next step after pre-processing is to determine the R-characteristic points (R-peaks) of the ECG signal [7]. To implement this procedure, the Pan-Tompkins algorithm is most often used [8]. This algorithm consists of step-by-step filtering of the signal first in the 5-30 Hz band, then the derivative of the received signal is searched for, for which the modular value is calculated, which is then re-filtered in the 0-15 Hz band, after which a threshold detector is used to find the position of the R-peaks. There are also modifications of the Pan-Tompkins algorithm, in which instead of finding the derivative after filtering the signal, the square of the signal is calculated [9]. Despite the fact that this algorithm is quite often used in various studies, recent works demonstrate its low efficiency [7, 10, 11] and show that the probability of correctly determining the position of the R-peak is 86.86%. This indicates the need to develop a new method for finding the positions of R-peaks in ECG signals, which will have a higher probability of correctly determining the position of these peaks. There is also another problem - the problems of methods for determining the position of R-peaks in the ECG signal. Since further processing depends directly on the accurate calculation of these positions, it is necessary to implement a method that will be resistant to nonlinear interference and distortions of the ECG signal when searching for the positions of R-peaks [7]. To solve this problem, it is proposed to perform a polyspectral analysis of ECG signals. A number of scientific works published today are aimed at developing a method for calculating polyspectrum using a time-frequency dynamic window [12, 13]. However, there are several limitations to the use of such algorithms, in particular, it is necessary to accurately determine the characteristic time scale taking into account their invariance in time. There is also considerable difficulty in normalizing the obtained polyspectrum, since the influence of discretization and random errors leads to the need for regularization. To overcome these shortcomings, the wavelet bispectrum and bicoherence were introduced to study the interactions between individual local oscillators in a complex dynamical system [14]. The generalization of the bispectrum to the wavelet transform makes it possible to analyze such fundamentally nonlinear phenomena as the temporal dynamics of the phase relationship between different harmonics in a signal [15], as well as to identify short-lived structures in sets of spatiotemporal data. Higher-order statistics based on wavelet analysis can be successfully used to study the behavior of systems with nonlinear dynamics and to isolate coherent structures.

Wavelet-bispectrum transform

The continuous wavelet transform of a signal f(x) has the following form [14, 15]:

$$W_{\psi}(a,b) = \frac{1}{\sqrt{C_{\psi}}}\int_{R} f(x)\psi^{*}_{ab}(x)dx \qquad (1)$$

where $\psi^{*}_{ab}(x) = \frac{1}{\sqrt{a}}\psi(\frac{x-b}{a})$; a and b are the scale and shift, respectively; ψ is the wavelet generating function, and C is the normalization coefficient.

The wavelet range (1) determines the behavior over time of the studied object of each time scale (a) at any time (b). The normalization coefficient C in formula (1) is defined as:

$$C_{\psi} = \int_{-\infty}^{+\infty} \frac{\left|\widehat{\psi}(w)\right|}{|w|} dw < \infty, \qquad (2)$$

where $\widehat{\psi}(w)$ is the Fourier transform of the wavelet $\psi(w)$.

Condition (2) for the constant $C\psi$ limits the class of functions $\psi(x)$ that can be used as basic wavelets. From formula (2) it follows that the function must be equal to zero at $\omega=0$ and, therefore, the wavelet must have a zero mean. Almost any function that satisfies condition (2) is a wavelet, so it is possible to choose the type of function depending on the specific problem. Each basic wavelet function $\psi(x)$ is characterized by different specific properties, which allows, using different wavelets, to identify the features of the signal. Among the many currently existing various wavelet functions, we will choose and use the complex Morlet wavelet [16], which is written as follows:

$$\psi(x) = \exp(jw_0 x)\exp(-x^2/2) \tag{3}$$

The classical estimation of the spectral power density, determined by various spectral methods, is useful in determining the independent contribution of each spectral component to the total spectrum of the time series signal. However, information about the possible connection of different frequency components with each other is not revealed. To obtain such information, polyspectral analysis is used, which allows to detect the effects of the relationship of spectral components. In particular, the wavelet bispectrum of the studied signal is determined by the following expression [12, 14]:

$$B(f_1, f_2) = \int_T W(f_3, b)W(f_2, b)W(f_1, b)\,, \tag{4}$$

where f_1, f_2 are the frequency indices a, b of the wavelet transform (1); $f_3=f_1+f_2$.

The use of the wavelet-bispectrum strategy in the study of the positions of QRS complexes should provide an increase in the accuracy of the selection of these positions against the background of interference, taking into account the main advantages of this approach in the ability to determine spectral components that have certain phase relationships. These components should be responsible for QRS complexes, while the spectral components of interference that do not have phase relationships should be suppressed in this assessment. The use of wavelet transforms will allow analyzing the behavior of these spectral components in time, thereby allowing to determine the positions of QRS complexes in time.

Results of research and their analysis

The MIT-BIH database [17] was used for the experimental studies. This database is one of the most widely used databases for the analysis of QRS complex detection methods in ECG signals [18]. The MIT-BIH database contains 48 half-hour segments of two-lead ambulatory ECG recordings obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. In addition, twenty-three records were randomly selected from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (approximately 60%) and outpatients (approximately 40%) at Beth Israel Hospital in Boston. The remaining 25 records were selected from the same set to include less common but clinically significant arrhythmias that would not be well represented in a small random sample. The recordings were digitized at a rate of 360 samples per second per channel with 11-bit resolution within a range of 10 mV. Two or more cardiologists independently annotated each received recording [19]. Accordingly, this database has an annotation indicating the position of QRS complexes, as well as signals that, due to the presence of pathologies in the rhythm, have non-stationary and nonlinear distortions. It is these distortions that ensure the active use of this database, since methods for searching for QRS complexes must be invariant to such non-stationary changes. Figure 1 shows an ECG signal for which it is necessary to calculate the positions of R-peaks.

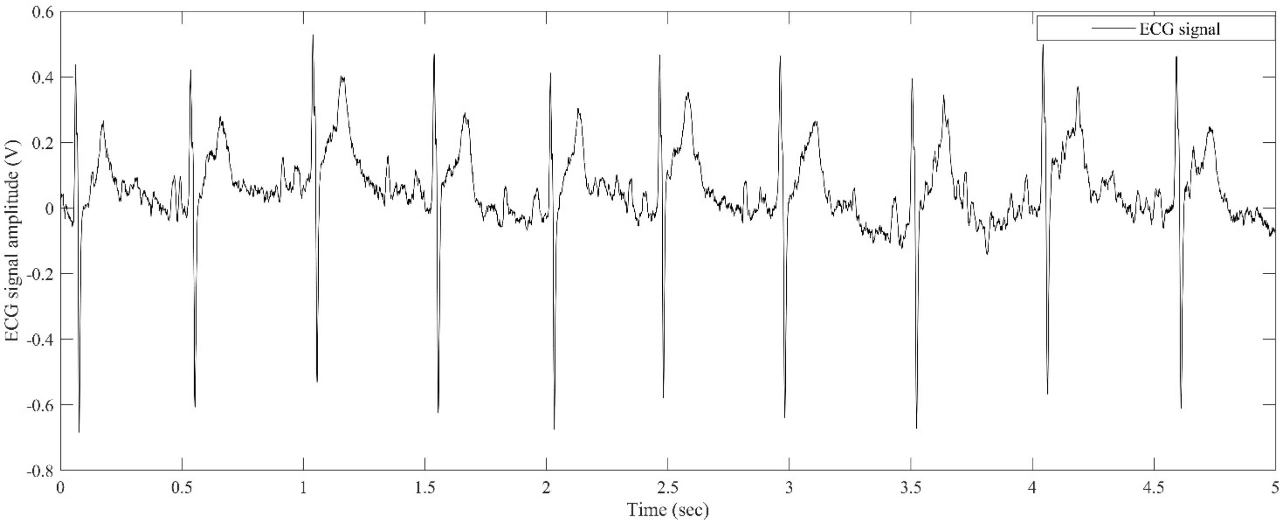

Figure 1 - One channel of ECG signal

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To study the wavelet-bispectrum method in order to estimate the position of R-peaks, it is necessary to calculate the continuous wavelet transform (1) for a given signal. Figure 2 shows the wavelet transform, Figure 3 shows the calculated wavelet bispectrum according to definition (4), using the wavelet transform shown in Figure 2. Figure 3 shows that after calculating the wavelet bispectrum, the noise level that was present in the wavelet transform in Figure 2 decreased.

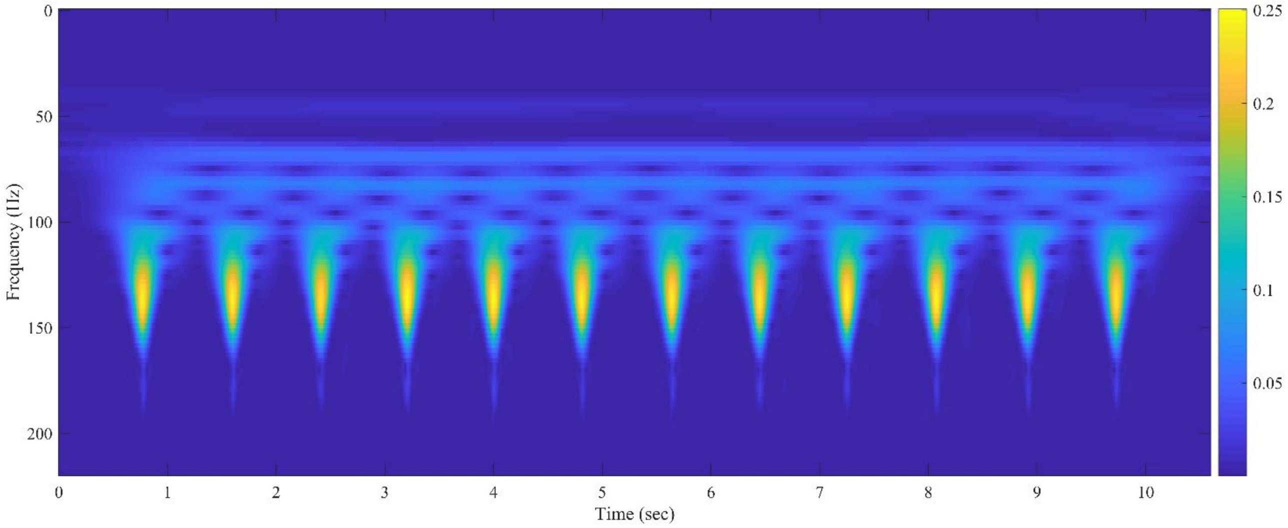

Figure 2 – Wavelet-Transform for ECG signal

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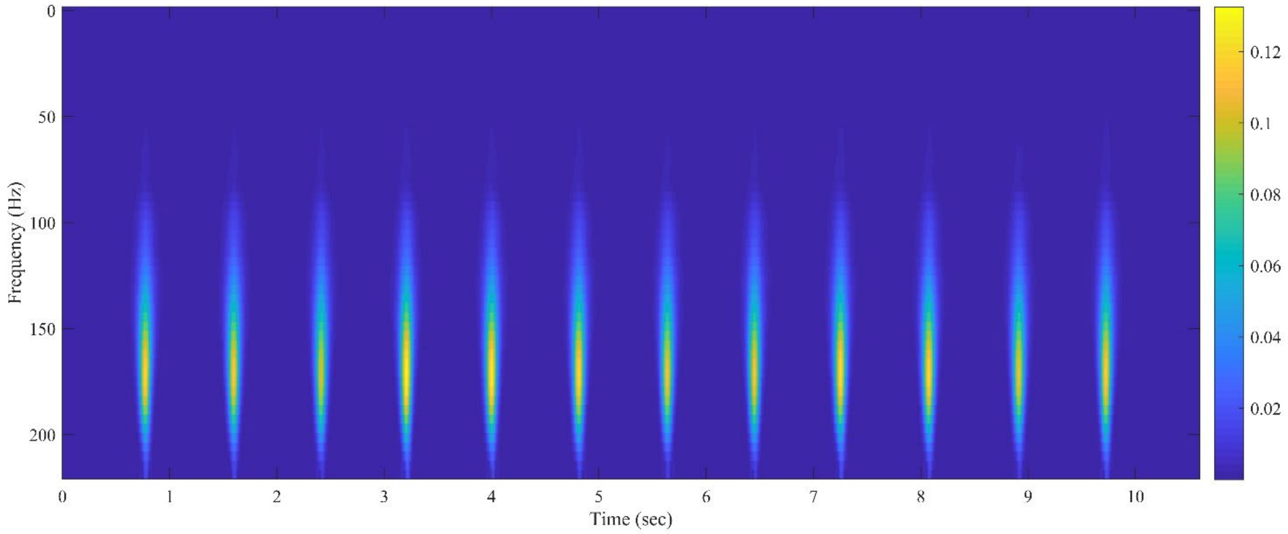

Figure 3 - Wavelet-Bispectrum for ECG signal

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This is explained by the peculiarity of bispectrum signal processing, which means that spectral components that do not have phase relationships will be removed. Noise components of the signal do not have such relationships, which is why they are absent in the wavelet bispectrum transform. It is also clear from the figures that the frequency characteristics have changed when using the wavelet bispectrum transform. To determine the positions of the R-peaks of the studied signal, it is necessary to determine the average values of the wavelet-bispectrum transform in each column of the wavelet-bispectrum matrix. To find the positions themselves, it is necessary to calculate the local maxima of the obtained function. Figure 4 shows the result of calculating the average in the wavelet-bispectrum estimate. Figure 5 shows the result of calculating the positions of the R-peaks together with the ECG signal.

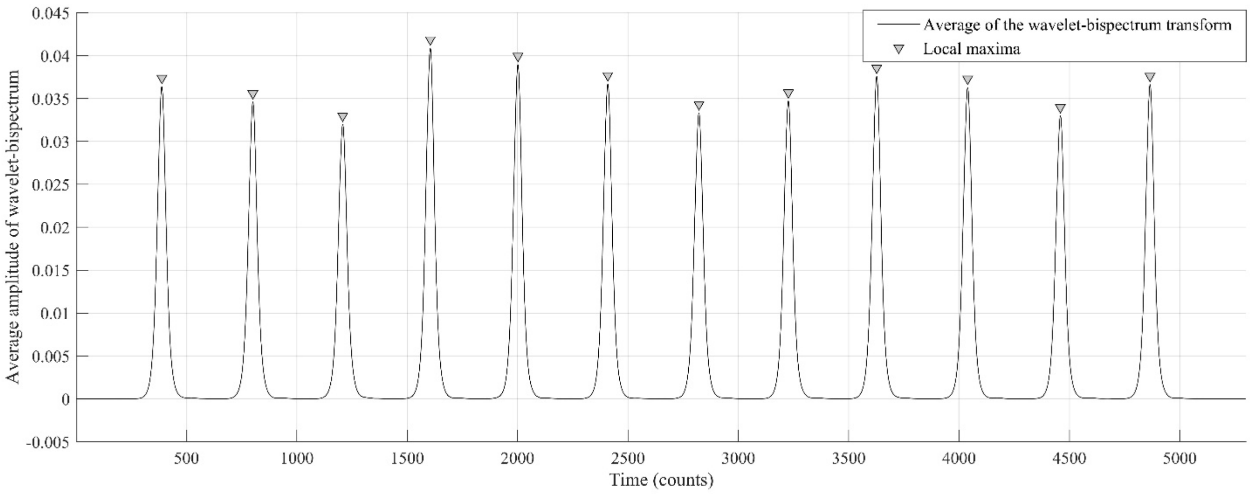

Figure 4 - Calculation of R-peak position by proposed method

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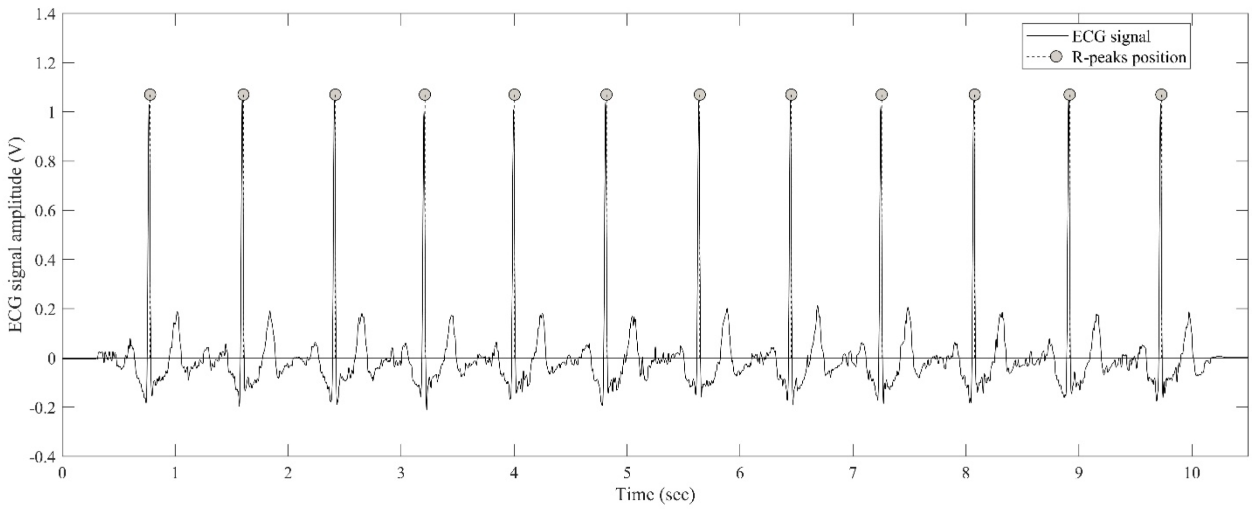

Figure 5 - The result of searching for R-peaks in the ECG signal

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One of the main problems of the proposed approach is the dependence on the length of the initial signal. If the signal being processed has a high duration, then the calculations of the wavelet-bispectrum will be much slower, due to the dependence of the number of frequency samples on the length of the signal in the wavelet transform, on which the dimension of the bispectrum will also depend. One of the options for avoiding such a problem is to use window processing, as was performed in the bispectrum estimate of the abdominal signal. Thanks to this application of procedures, the method becomes invariant to interference, can search for distorted, non-stationary QRS complexes, and allows processing of long-term recordings.

For comparison, Figure 6 shows the result of the calculation on the same signal using the Pan-Tompkins algorithm [8].

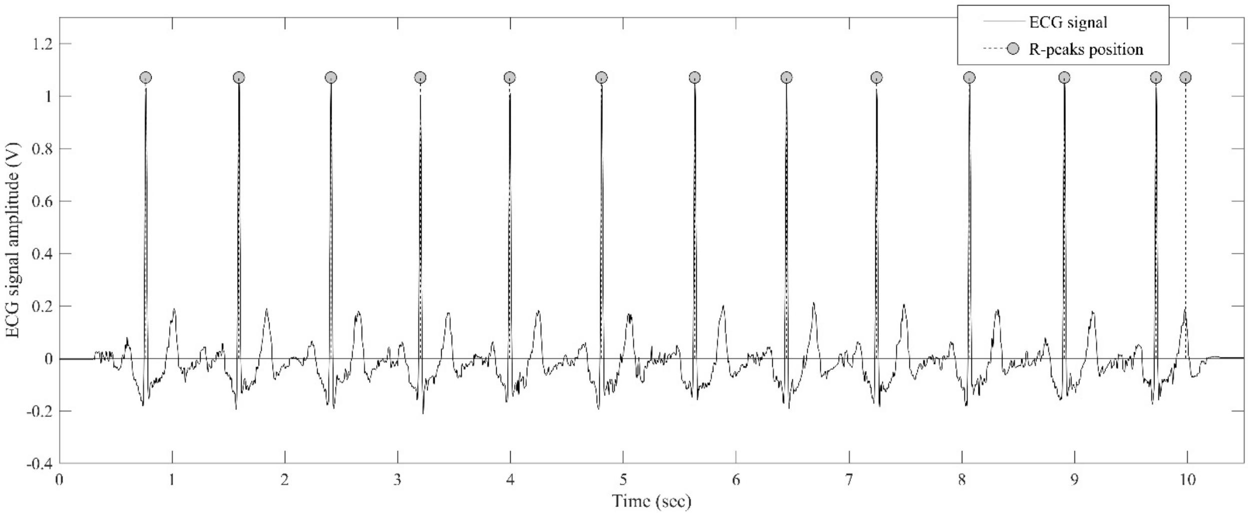

Figure 6 - The result of searching for R-peaks in the ECG signal using the Pan-Tompkins method

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As can be seen from the results in Figure 6, when using the Pan-Tompkins method, an extra position was found that does not correspond to the position of the R-peak. This problem can be eliminated by adding to the algorithm the minimum distance that should be between neighboring R-peaks, then the extra positions will be ignored. For comparison, Figure 7 shows the calculation of the squared signal modulus in the 0-15 Hz frequency band for another signal - this is the penultimate procedure in the Pan-Tompkins algorithm. Figure 8 shows the result of calculating the average wavelet bispectrum for the same set of signals that were used to calculate the squared signal modulus shown in Figure 7. As can be seen from the comparison of Figures 7 and 8, the use of the wavelet bispectrum method and the Pan-Tompkins method for finding R-peaks give results that are very different. It is worth noting that the wavelet bispectrum approach provides noise suppression. Figure 9 presents the result of searching for R-peaks using the Pan-Tompkins method, for the modulus of the square of the signal values in the 0-15 Hz band, which was shown in Figure 7.

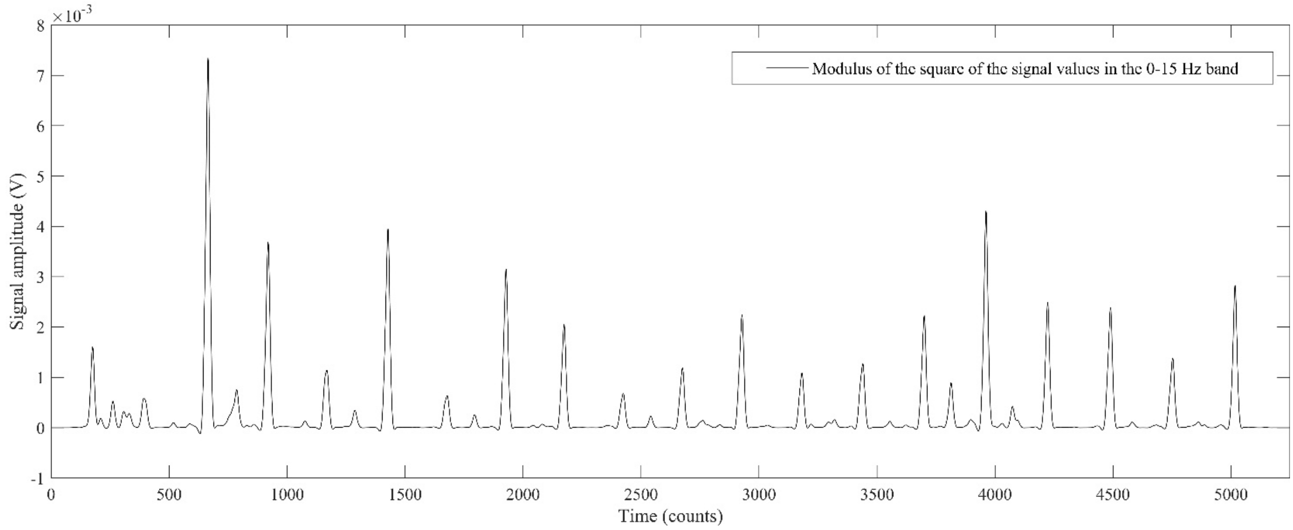

Figure 7 - The result of the penultimate procedure of the Pan-Tompkins algorithm

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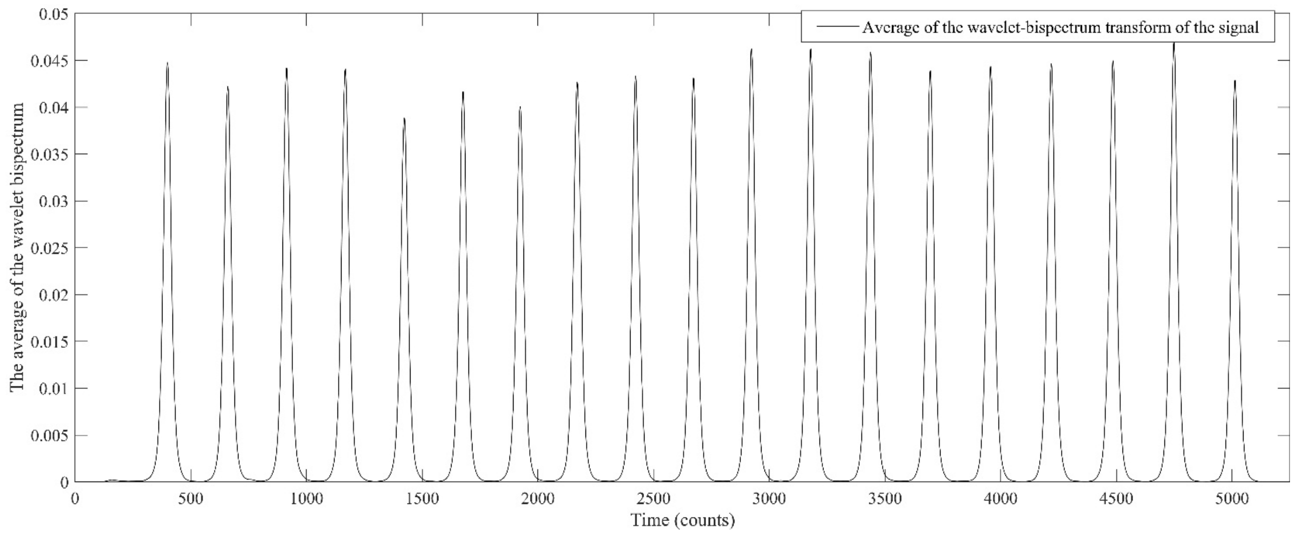

Figure 8 - Result of calculating the average value of the wavelet-bispectrum in finding the position of R-peaks

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Figure 10 presents a similar calculation result, but using the wavelet-bispectrum method, the penultimate procedure of which was demonstrated in Figure 8.

The problems of the Pan-Tomkins algorithm were caused by the search for the average value of the square root of the signal values in the 0-15 Hz band between all available signal channels. Because of this, one of the channels, which contains the largest noise contribution, distorted the results of the search for the position of R-peaks in the ECG signal. This problem can be solved by using adaptive methods for estimating the level of interference in the signal, thereby determining the channels with the highest level of interference, which when using this algorithm would be removed and not used. However, the use of the wavelet-bispectrum method also uses the averaging procedure between channels, but not signals or their modulus values, but the averaging of wavelet transforms for each channel is used, thereby providing even greater noise immunity of this method.

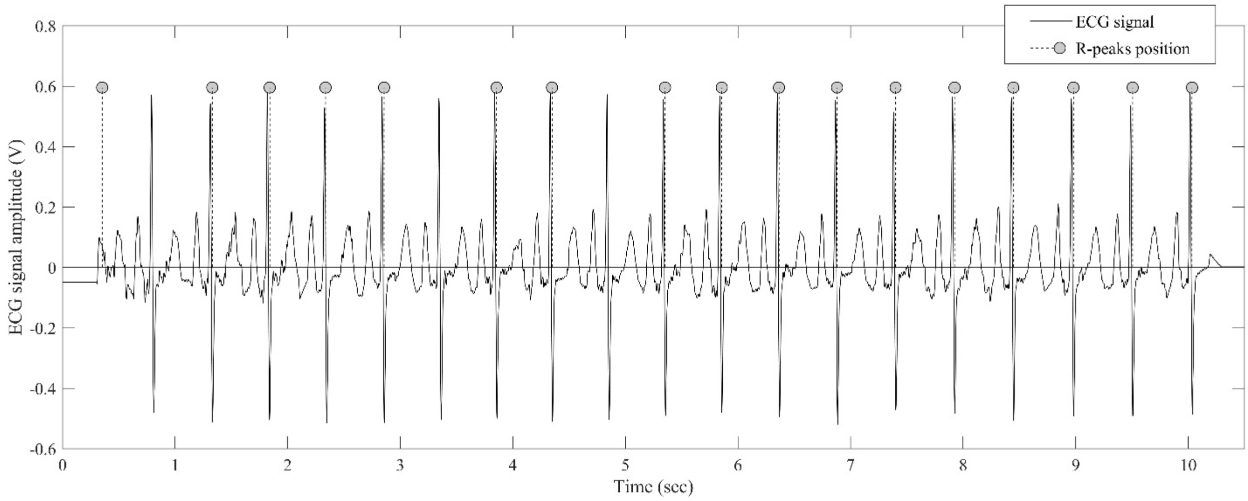

Figure 9 - Result of calculating the position of R-peaks in the Pan-Tompkins algorithm

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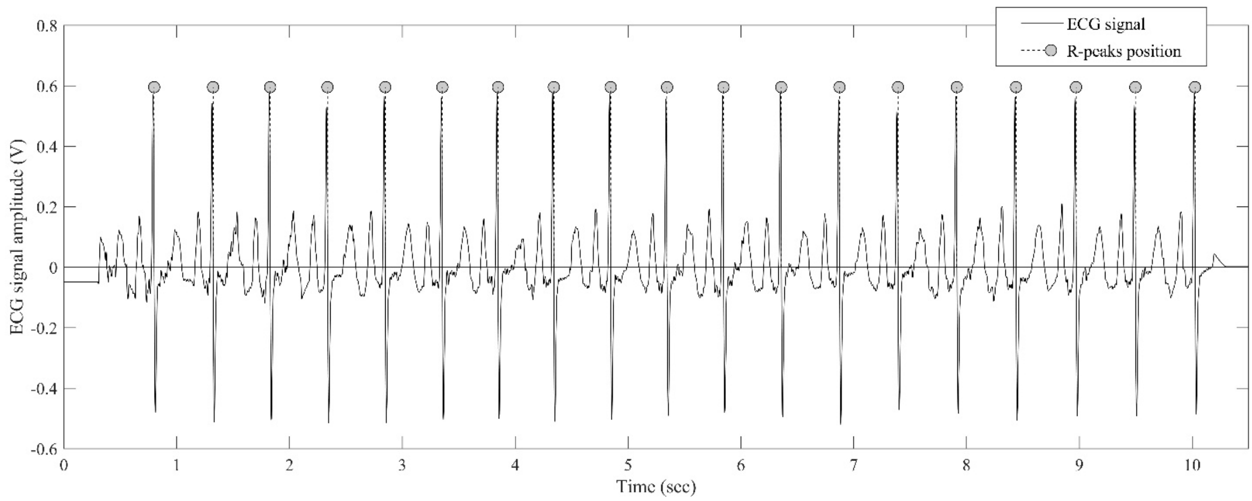

Figure 10 - Result of calculating the position of R-peaks using the wavelet-bispectrum algorithm

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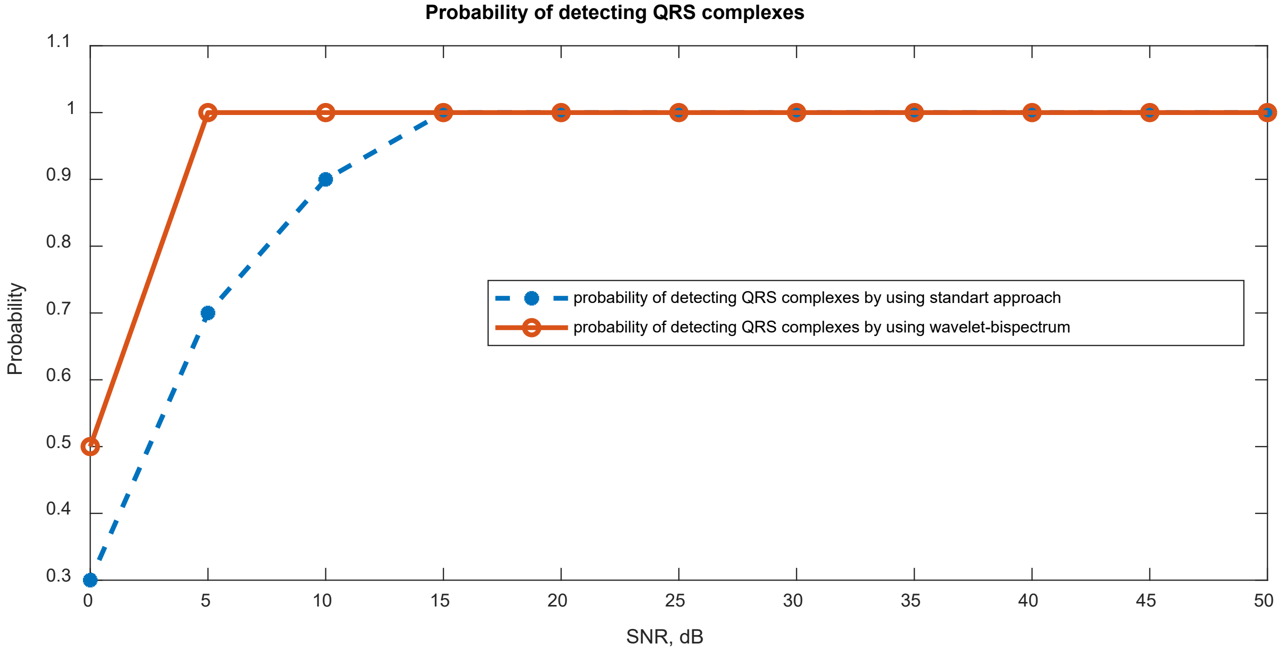

Figure 11 - Result of calculating the noise immunity of two methods

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Even though Figures 9 and 10 demonstrate the results using the averaging procedures of all available channels without prior study of the level of interference in each of them, the wavelet-bispectrum algorithm showed a better result. Due to averaging in the channel with the highest noise level in the Pan-Tompkins algorithm, errors occur in determining the positions of R-peaks. That is, the Pan-Tompkins algorithm is less noise-resistant than the proposed wavelet-bispectrum method. Figure 11 shows the results of the noise-resistant study of these two methods.

Figure 11 shows the results of the noise immunity assessment of the wavelet-bispectrum method with an orange line, and the dashed blue line for the Pan-Tompkins algorithm. The results demonstrate that the wavelet-bispectrum method allows for the search for the position of R-peaks with a probability of 100% for the signal-to-noise ratio in the range from 5 to 15 dB of values, when the Pan-Tompkins algorithm at a given level does not allow for a one hundred percent determination of their positions. Table 1 presents the results of the study of the effectiveness of the wavelet-bispectrum method, which was tested on the MIT-BIH database. A comparison with other methods is also demonstrated. The following parameters are used to study the effectiveness: correctly determined position (TP), incorrectly determined position (FP), missed position (FN), as well as the sensitivity of the method, which is determined using the following equation and estimates the probability of correct determination of the positions of QRS complexes [7]:

$$Sensetivity = \frac{TP}{TP + FN} \times 100\% \tag{5}$$

The results were verified using the Pan-Tompkins (P-T) methods [8], the MC-Dropout uncertainty method [20], the deep ensembles (5-Ensemble) [21], and the PN-QRS method [10], as well as the developed wavelet-bispectrum (W-B) method

Table 1 - Results of the efficiency of determining the position of R-peaks

Method	TP, number	FP, number	FN, number	Sensitivity, %
P-T	101469	5828	7965	92.72
MC-Dropout	108967	137	467	99.57
5-Ensemble	109238	30	196	99.82
PN-QRS	109340	24	94	99.91
W-B	109396	4	38	99.96

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The conducted studies demonstrate that the results obtained for the MIT-BIH database are better than the results of other authors, and the sensitivity of the proposed method reaches 99.96%, which indicates the high efficiency of this method. One of the main problems of the proposed approach is the dependence on the length of the initial signal. If the signal being processed has a high duration, then the calculations of the wavelet bispectrum will be much slower, due to the dependence of the number of frequency samples on the signal length in the wavelet transform, on which the dimension of the bispectrum will also depend. The higher it is, the longer the calculations are performed. One of the options for avoiding such a problem is to use window processing. When implementing the proposed method, this feature was taken into account and corrected by segmenting the signal and processing local fragments. Also, for a better calculation, a comparison of signal fragments in the found positions of QRS complexes has been added, after which a correlation analysis of the found fragments is performed, and fragments that have a correlation by modulus lower than 0.3 are removed and not taken into account as QRS complex positions. Using this feature in processing, QRS complexes with distortions are not taken into account, which can lead to omissions in their definition. Because of this problem, it was decided to use a correlation analysis of signal fragments in such a way that fragments with distortions are stored in an additional variable, after which, if there were several of them, a correlation analysis of these fragments is performed; if they have a degree of correlation by modulus greater than 0.7, then these fragments are also considered as QRS complex positions. Thanks to this application of procedures, the method becomes invariant to interference, can search for distorted, non-stationary QRS complexes, and allows processing of long-term recordings.

Conclusions To improve the accuracy of determining the R positions of characteristic points of the ECG signal, a wavelet-bispectrum method for determining their positions was developed. The results of experimental studies demonstrate 99.96% sensitivity of determining the R-peak position for the MIT-BIH signal database. The use of the newly developed algorithm increased the sensitivity of determining the R-peak position by 7.24% compared to the basic Pan-Tompkins algorithm.

Supplementary Materials: Software code for generation of ECG signals and interferences is available by https://sameni.org/OSET/. Algorithms necessary for implementation of proposed technique are represented in the paper.

Author Contributions: Conceptualization, O.V. and A.T.; methodology, A.T.; software, O.V.; validation, O.V.; formal analysis, A.T.; investigation, A.T.; resources, A.T.; data curation, A.T.; writing—original draft preparation, O.V.; writing—review and editing, A.T.; visualization, O.V.; supervision, A.T.; project administration, A.T.

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