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RESEARCH AND PROCESSING OF ECG SIGNALS USING DISCRETE AND CONTINUOUS WAVELET ANALYSIS

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Abstract. The publication is devoted to analyzing electrocardiogram signals of artificial origin of realistic form with the possibility of controlling the duration, sampling frequency, noise level and pulse rate using Ingrid Daubechies wavelets. The synthesized signals were investigated using discrete wavelet analysis to study the influence of these parameters on the approximation and detail coefficients. The priority influence of noise on the detail coefficients and the dependence of the number of signal peaks on the given parameters were established. The article uses for the first time the method of packet discrete wavelet filtering of detail coefficients and approximation coefficients. This allowed to provide a high degree of signal restoration to the original form. Similar studies were conducted for continuous wavelet transformation with the generation of wavelet scalogram images, which provide additional diagnostically significant information. The results obtained in the form of an algorithm are promising for use in analyzing signals from radar systems. The developed model for generating realistic-shaped signals is more efficient and exceeds the average accuracy (96.2 %) compared to analogues (88.03 %). The effectiveness of the developed method is fully confirmed by the correlation matrix of functions of discrete spectra of artificial ECG signals.

Keywords: Electrocardiogram (ECG), wavelet transform, packet wavelet filtering, approximation coefficients, detail coefficients, packet filtering, classification.

INTRODUCTION

The principles of filtering and processing an electrocardiogram (ECG) signal are similar to those used in radio engineering (noise removal, spectral analysis, etc.) [1]. The accuracy of ECG signal analysis determines the correct diagnosis [2]. During ECG signal acquisition, various noises such as transmission line interference, baseline deviation, motion, and noise distort the ECG signal [3]. Since the ECG signal is non-stationary, it is pretty challenging to remove these noises from the recorded ECG signal [4].

Algorithms for processing cardiac signals are very diverse. Among the well-known methods of ECG processing, wavelet analysis can be distinguished. Unlike processing cardiograms using bandpass filters, wavelet transforms can accurately record both time and information about the frequency of the cardiac signal. The essence of the wavelet analysis method is that the cardiac signal using the wavelet transform is decomposed into approximating and detailing coefficients [5]. They are responsible for the low-frequency and high-frequency components of the signal, respectively [6]. After processing, the signal is a reconstruction of the signal using approximation and detail coefficients [6].

The study's authors [3] conducted a comparative analysis of noise reduction using discrete wavelet transform and various noise reduction methods (low-pass filtering, high-pass filtering, empirical mode decomposition, Fourier decom-position method of ECG signal distorted by noise). The signal-to-noise ratio, root-mean-square difference, and root-mean-square error were used as evaluation criteria. The experiment result showed [3] that the proposed ECG denoising method based on discrete wavelet transform outperformed other electrocardiogram signal denoising methods because more components of the ECG signal are preserved than other de-noising algorithms.

The development of the wavelet analysis theory of electrocardiogram (ECG) signals is a promising research direction. The existing theory needs further development to simplify the processing of ECG signals. The research results can be applied to the analysis of radar system signals.

ANALYSIS OF AREAS OF RESEARCH AND STATEMENT OF THE PROBLEM

Classification of ECG signals is a challenging task due to a number of technical, medical, and practical challenges. ECG signals have high variability between different patients, which makes it difficult to create universal recognition algorithms. A model for generating artificial electrocardiogram (ECG) signals of realistic shape is important for training artificial intelligence models, as it allows expanding the volume and variety of training data under controlled conditions.

The second significant problem is the presence of noise and artifacts in the recordings [3]. The ECG signal is very sensitive to body movements, problems with electrode contacts, or electrical interference. Such distortions can affect the accuracy of classification, so the signals need filtering and preprocessing before analysis [2]. Artificially generated ECG signals allow for precise control of heart rhythm parameters, arrhythmia types, heart rate, etc., which enables AI training on a wide range of clinical scenarios, including rare pathologies that are difficult to collect in real data. This is especially important for building diagnostic systems with high sensitivity and specificity.

Many machine learning methods require a uniform length of input data, but when trimming or scaling ECG signals, important information can be lost. Many open databases are created in conditions far from real clinical practice and do not take into account many of the variations that doctors encounter in their daily work [4]. The use of real medical data is associated with ethical and legal restrictions.

Using a model to generate artificial electrocardiogram signals is similar to the image augmentation method widely used in computer vision. In the case of image recognition, in order to increase the accuracy and robustness of the neural network, modified versions of real images are added to the training set – they are changed in brightness, rotated, scaled, mirrored, etc. [7]. This allows the model to better generalize information and cope with new input variants. Similarly, in the case of ECG, artificially generated signals are "augmented" variants of cardiac activity that allow the AI model to "see" more examples, including those that are rare or have unclear manifestations in real patients. This is especially important in medicine, where a diagnostic error can have critical consequences. Thus, the generation of synthetic ECGs is a form of data augmentation that increases the quality and reliability of

AI-based systems. The use of artificially generated signals in combination with real data provides a more balanced, complete and scalable training of artificial intelligence models in medicine.

The use of wavelet transforms in the analysis and processing of electrocardiogram (ECG) signals is considered one of the most effective methods due to its unique properties that prevail over traditional approaches such as fast Fourier transform (FFT), filtering or principal component analysis (PCA).

The most comprehensive review of publications for the period 2011–2020 devoted to ECG signal processing algorithms using wavelet transforms is given in the work of researchers D. Darwan and H. Mustafidah [4]. The authors note that the most important aspect of ECG research in the future may be the use of datasets, as well as feature extraction and classifications taking into account the level of accuracy [8].

Wavelet transform has the ability to simultaneously analyze signals in both the time and frequency domains. This is especially important for ECG signals that are non-stationary, that is, they contain important information in individual short-term signal sections (e.g., P, QRS, T waves). Traditional methods, such as FFT, provide only the frequency spectrum and lose time localization, which critically reduces the accuracy of diagnosis. Studies [9, 10] contain data confirming the effectiveness of using wavelet transform to extract features of ECG signals with an accuracy of about 95.5 %−98.38 %.

Wavelets allow for multi-level decomposition of the signal, dividing it into different scale components. This allows you to accurately isolate noise, artifacts or interference without distorting the most important elements of the ECG. For example, high-frequency noise can be effectively filtered at the appropriate decomposition level, while maintaining the clarity of the QRS complex [11].

Many studies and practical implementations of artificial intelligence systems based on ECG signals show that wavelet features provide higher accuracy in classifying heart pathologies compared to features obtained using other methods [11–13]. Machine learning algorithms trained on wavelet representation of the signal demonstrate better results in the detection of arrhythmias, ischemia, atrial fibrillation, etc.

The authors of the study [14] used a semi-synthetic ECG dataset with artificial baseline deviations superimposed. The authors generated twelve baseline deviations, including sinusoids, peaks, and step functions. The authors implemented and evaluated 14 common wavelets up to 12 levels. The evaluation criterion was the mean square error (MSE) between the original ECG fragment and the processed signal with the artificial deviation removed [14].

In the work [15], the authors proposed a model based on ECG signal processing using the discrete wavelet transform (DWT). The decomposition first removes noise in the signal, then extracts statistical features from the noise approximation coefficients of the signal, and finally classifies the data using cross-validation for greater confidence.

The analysis result is affected by the type of wavelet chosen for analysis. In the research paper [16], noise removal using different levels of wavelet transformation (DWT) decomposition based on different types of mother wavelets, such as orthogonal (Haar, Daubéchy, Coiflet, Simmle) and biorthogonal, is analyzed and compared. The studies used cardiac signals cleaned of low-frequency noise, so we cannot speak about the full applicability of the method to the processing of real cardiograms.

In [17], a wavelet packet filtering algorithm was developed, which included moving along the branches of the wavelet packet tree with a restriction on each branch of approximation and detailing the coefficients at the time of achieving the minimum mean square error. The possibility of applying the method to the 20 most frequently used signals was investigated, but data on the application of this approach to ECG processing are missing.

Effective wavelet filtering of real signals is impossible without determining their shape. The shape of a real signal is related to its wavelet spectrum. In [18] it was proposed to use continuous color wavelet scalograms for analyzing the waveform. The disadvantage of a continuous wavelet spectrogram is the complexity of analyzing a blurred color image. To eliminate this disadvantage, we used a technique based on the comparative analysis of signal spectrograms and correlation matrices, which are calculated by the formula using mathematical functions of the coefficients of discrete wavelet spectra [18]. This method was tested on 20 of the most common signals. The method has proven its effectiveness and efficiency, but electrocardiogram signals have not been studied.

Modern evidence-based medicine allows the use of non-trivial algorithms for analyzing and interpreting ECGs only after thorough testing on test signals that adequately reflect the entire spectrum of signals possible in reality [19]. The problem of generating test signals that simulate real electrocardiogram signals is no less significant than the choice of wavelet analysis parameters [20].

One of the well-known methods of such verification is testing algorithms using artificial signals that simulate a variety of real ECGs of normal and pathological form [21]. Today, there are many models for generating synthetic ECG data for use as test sets.

Examples of such generative ECG signal models are presented in [22–24]. Most of the methods for generating test signals initially used transformations such as dithering and warping [22]. However, these methods simply modify the original signal, which leads to poor diversity in the generated samples.

Recently, the synthesis of artificial ECGs based on deep learning models has become widespread. The authors of [23] use generative adversarial networks (GANs) to obtain synthetic ECG data that are difficult for humans to distinguish from experimental data. The resulting dataset was used to train and evaluate a denoising autoencoder that achieves state-of-the-art filtering quality of ECG signals. In [24], it is shown that the generated data improves the performance of the model compared to a model trained only on experimental data.

Previous studies have shown that the performance of recent computerized ECG interpretations is comparable to that of expert physicians, with correct classification rates of 91.3 % for the computer program and 96.0 % for cardiologists, respectively [25].

An example of one model for generating synthetic ECG data is the project [26]. This program for generating artificial cardiac signals has a significant drawback due to the limited variability of the input parameters (noise characteristics and a limited wavelet base). However, the main drawback that prevents the use of the model for signal generation is the lack of a function that limits the wavelet coefficients by the level of decomposition and reconstruction.

Also, wavelet transform scales well and is suitable for both offline and real-time analysis, which makes it an ideal tool for embedded cardiac monitoring systems. Thus, wavelet transform provides high accuracy, flexibility, and efficiency in processing complex medical signals, especially ECG, and is therefore rightfully considered one of the best methods in modern biomedical engineering and diagnostics.

The purpose of this article is to further develop the theory of wavelet analysis of ECG signals to improve the quality of signal analysis in medical information systems for the detection of cardiac pathologies at early stages.

MATHEMATICAL MODEL OF DISCRETE WAVELET TRANSFORMATION AND FILTERING OF ARTIFICIAL ELECTROCARDIOGRAM SIGNAL FROM NOISE

For research and analysis, the article uses a generative model of electrocardiogram signals of artificial origin of a realistic form. The difference between the created model and that considered in the literature review [26] is the ability to control the duration, sampling frequency, noise level, and pulse rate using Ingrid Daubechies wavelets to simulate (Fig. 1).

A signal with additive Gaussian noise can be described by the relation:

$$f_\eta(t_i) = f(t_i) + \eta\,, \tag{1}$$

where $f(t_i)$ – is the signal function; $f_\eta(t_i)$ – function of signal with noise; η – white normally distributed noise.

Wavelet decomposition of the signal $f_\eta(t_i)$ into levels for the approximation and detail coefficients is determined by a system of equations [27]. For signals without the influence of noise, can use a system of equations that has the form:

$$\left.\begin{aligned} a_{j+j_0,k} &= \int_R f(t_i)\cdot\varphi_{j+j_0,k}(t)dt \\ d_{j+j_0,k} &= \int_R f(t_i)\cdot\psi_{j+j_0,k}(t)dt \end{aligned}\right\} \tag{2}$$

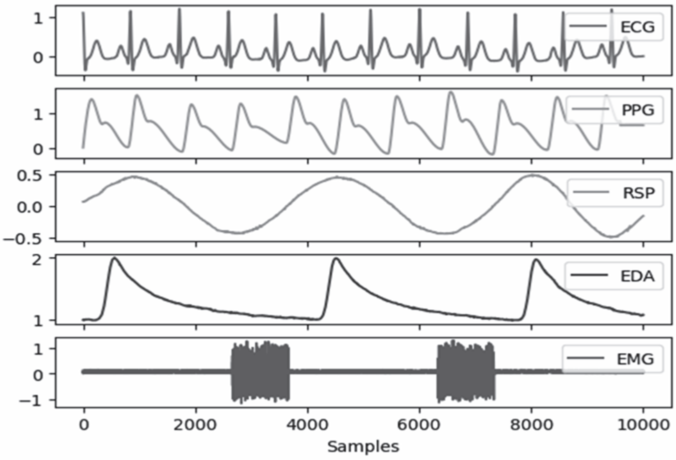

Fig. 1. Possibilities of a generative model of artificially generated electrocardiograms of realistic shape compared to the model [26]

For signals with additively added noise, the system of equations for the approximation and detail coefficients is as follows:

$$\left.\begin{aligned} \overline{a}_{j+j_0,k} &= \int_R f_\eta(t_i)\cdot \varphi_{j+j_0,k}(t)dt \\ \overline{d}_{j+j_0,k} &= \int_R f_\eta(t_i)\cdot \psi_{j+j_0,k}(t)dt \end{aligned}\right\} \qquad (3)$$

In expressions (2), (3) R – domain of definition $f(t_i), f_\eta(t_i)$; $\overline{a}_{j+j_0,k}, \overline{d}_{j+j_0,k}$, $a_{j+j_0,k}, d_{j+j_0,k}$ – coefficients of approximation and detail under the influence of noise, respectively; $\varphi_{J+J_0,k}(t), \psi_{J+J_0,k}(t)$ – “maternal” and “paternal” wavelets, respectively; j_0, j, k – initial, flow and serial number of wavelet coefficients.

Using a generative model of electrocardiogram signals, we synthesize an artificial electrocardiogram signal with a minimum noise level $noise = 0.001$, the discrete wavelet decomposition of which is shown in Fig. 2. Let us change the level of superimposed noise ($noise = 0.5$), a discrete wavelet decomposition of such an electrocardiogram is shown in Fig. 3.

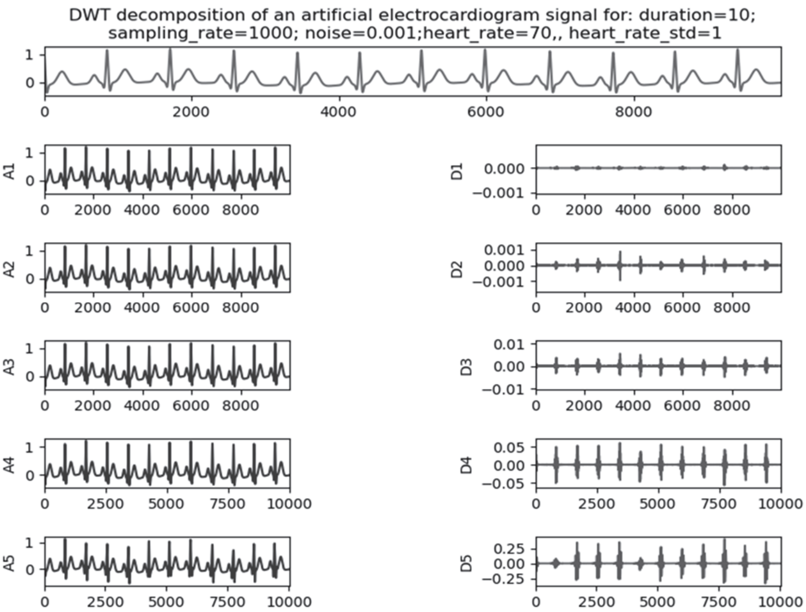

Fig. 2. Discrete wavelet decomposition of an artificial electrocardiogram signal with a minimum noise level noise = 0.001

Signal reconstruction function using wavelet decomposition coefficients:

$$\tilde{f}(t_i) = \sum_k \overline{a}_{j+j_0,k}\cdot\varphi_{j+j_0,k}(t) + \sum_{j=1}^{J}\sum_k F(\lambda)\cdot \overline{d}_{j+j_0,k}\cdot \psi_{j+j_0,k}(t), \qquad (4)$$

where $\tilde{f}(t_i)$ – is the function of the noise-free signal; $F(\lambda_j)$ – threshold function λ_j; $\varphi_{j+j_0,k}(t), \psi_{j+j_0,k}(t), F(\lambda_j)$ – parameters of discrete wavelet-filtering to ensure minimal error [11]:

$$E = \frac{1}{N} \cdot \sum_{i=1}^{N} (\tilde{f}(t_i) - f_\eta(t_i))^2, \qquad (5)$$

where E – the minimum mean square filtering error or MSE model.

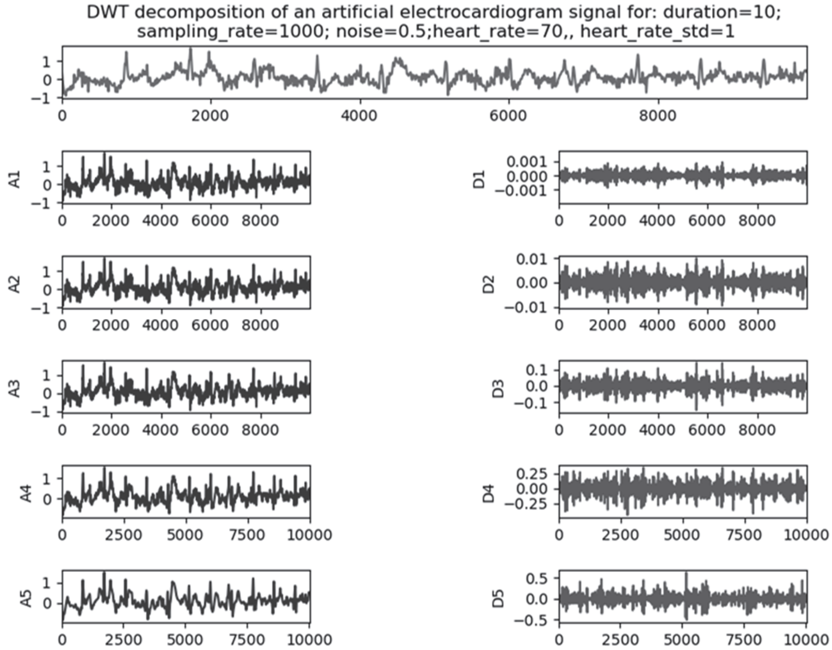

Fig. 3. Discrete wavelet decomposition of an artificial electrocardiogram signal with noise level noise $= 0.5$

For analysis, we compare the amplitudes of the discrete wavelet decomposition of the cardiogram with minimal noise (0.001) and a noise level of 0.5 (Fig. 4). It is noteworthy that the increase in noise level is characterized by an increase in the number of peaks (from 11 to 14 peaks).

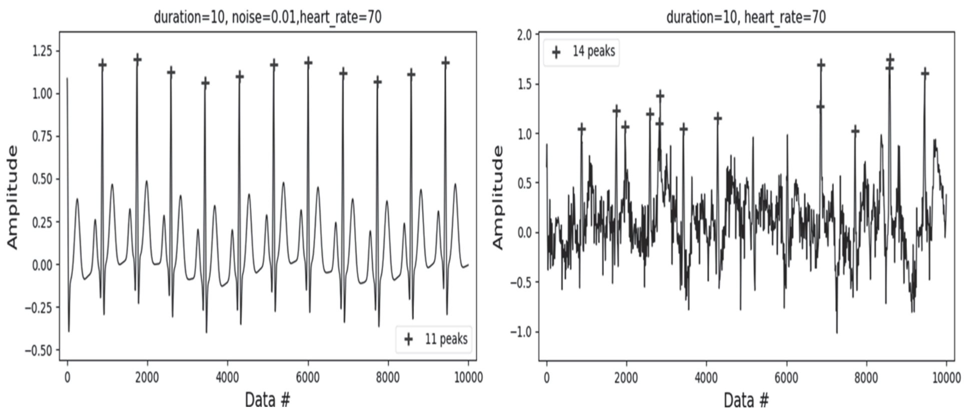

Fig. 4. Comparison of amplitudes and number of peaks of signals, the discrete wavelet decomposition of which is shown in Figs. 2 and 3

FIRST ALGORITHM FOR PACKET WAVELET FILTERING OF ARTIFICIAL ELECTROCARDIOGRAM SIGNAL

It should be noted that noise affects both the detailing and approximation coefficients (Fig. 3), and dramatically distorts the informative signal peaks (Fig. 4).

In the batch algorithm, both approximating $a_{j_0,k}$ and detailing $d_{j_0,k}$ coefficients are also calculated according to Mull's algorithm (Fig. 5). The application of packet wavelet filtering is described in detail in [27]. However, the studies were carried out using relatively simple signals. The essence of the method is that when decomposing the wavelet function of each subsequent level n, we obtain from the wavelet functions of the previous level, forming a tree structure with nodes and branches [27]:

$$\varphi = \sum_n h_n \varphi(t-n), \psi = \sum_n g_n \psi(t-n), \quad (6)$$

where h_n – are the low-pass filter coefficients for the current level of decomposition; g_n – high-pass filter coefficients for the current level of decomposition (Fig. 5).

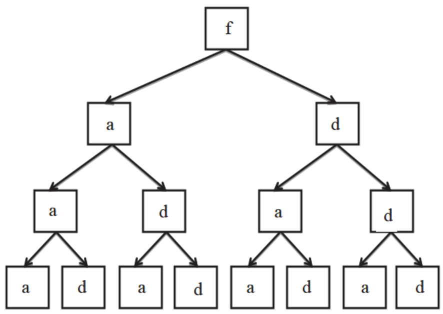

Fig. 5. Wavelet-packet decomposition

This allows you to obtain narrow ranges in the high frequency region and control the high frequency region of the signal (Fig. 6). In case different types of signals exhibit different frequency characteristics, this difference in behavior is reflected in one of the frequency subbands. By generating a feature from each subband and using the feature set as input to the classifier (random forest, gradient boosting, logistic regression, etc.), the classifier distinguishes between different types of ECG signals. Additional features can be obtained using special functions.

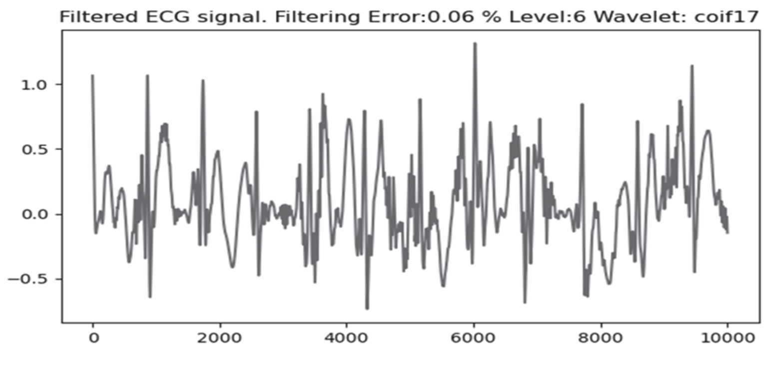

Fig. 6. A signal filtered by the wavelet packet filtering method, the decomposition of which is shown in Fig. 3

We rewrite relation (4) taking into account (6) in the form:

$$\hat{f}(t)=\sum_{j=1}^{J}\sum_{k}\left[F\left(\lambda_j\right)\bar{a}_{j+j_0,k}\varphi_{j+j_0,k}(t)\right]+\sum_{j=1}^{J}\sum_{k}\left[F\left(\lambda_j\right)\bar{d}_{j+j_0,k}\psi_{j+j_0,k}(t)\right], \quad (7)$$

It should be noted that the filtering error is extremely low, 0.06 %, which is determined not by relation (3), but using the Euclidean norms of vectors of time series of compared signals depending on the level of decomposition Level = 6 and wavelet coefficient coif17, obtained from the condition of minimum values in the system:

$$\left.\begin{aligned}\delta_j^d&=\frac{\|\sum_{j_o}^{J}\sum_{k}\bar{d}_{j+j_0,k}-\sum_{j_o}^{J}\sum_{k}d_{j+j_0,k}\|}{\|\sum_{j_o}^{J}\sum_{k}d_{j+j_0,k}\|}\\ \delta_j^a&=\frac{\|\sum_{j_o}^{J}\sum_{k}\bar{a}_{j+j_0,k}-\sum_{j_o}^{J}\sum_{k}a_{j+j_0,k}\|}{\|\sum_{j_o}^{J}\sum_{k}a_{j+j_0,k}\|}\end{aligned}\right\} \quad (8)$$

where δ_j^d,δ_j^a – are the relative errors of the wavelet-coefficients; $\|...\||$ – designation of the Euclidean norms of the corresponding vectors.

It should be noted that the use of packet wavelet filtering when processing a noisy electrocardiogram allows one to isolate only significant peaks (Fig. 7).

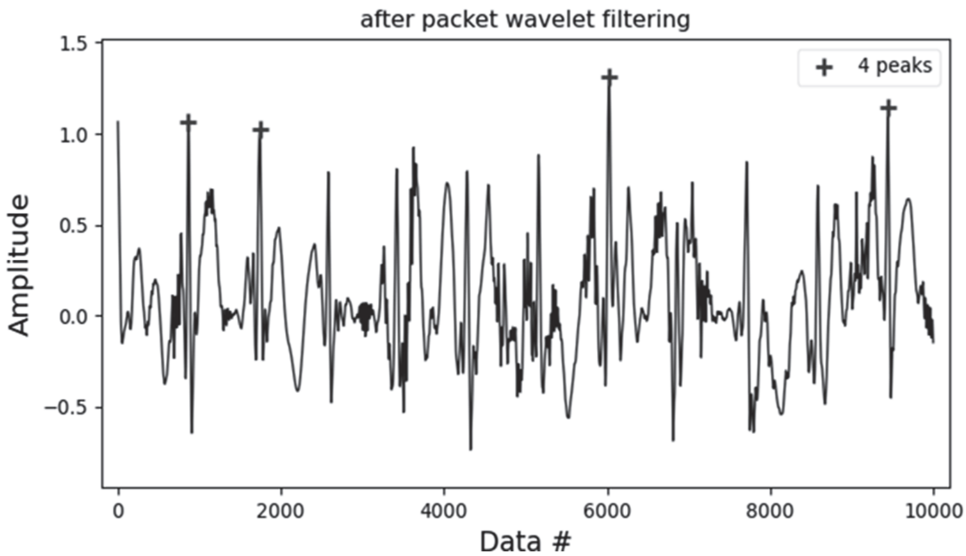

Fig. 7. Peaks of the filtered signal shown in Fig. 6

It should be noted that the main difference between using packet wavelet filtering of cardiogram signals and existing filtering methods is the possibility of identifying the most informative signal peaks in the time series of wavelet coefficients with smoothing of bursts that do not carry information (Fig. 8).

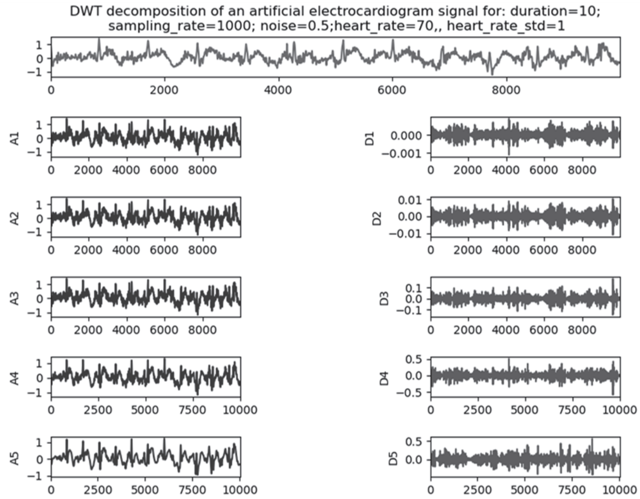

Fig. 8. Decomposition of a noisy artificial signal filtered by the wavelet packet method

MATHEMATICAL MODEL OF CONTINUOUS WAVELET TRANSFORM CWT USING EXPERIMENTAL DATA

Wavelet-analysis should be carried out according to the well-known relationship for a continuous local wavelet-spectrum [17, 28]:

$$W_{(a,b)} = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt, \tag{9}$$

where *x(t)* – is a signal with a random component; $\psi\left(\frac{t-b}{a}\right)$ – basic wavelet; $a \neq 0$ – scale parameter; $b \geq 0$ – shift parameter.

The data under study is discrete, so we write formula (9) in the form, selecting two arrays for scales *coeffs* for shifts *fred*:

$$coeffs, fred = \frac{\Delta t}{\sqrt{a}} \sum_{i=0}^{N-2} x(t_i)\psi\left(\frac{t_i - b}{a}\right). \tag{10}$$

Since when analyzing artificial signals, the scale is of greater interest than the shift, then to eliminate the dependence of the results on the shift b, use the representative amplitude of scale inhomogeneity $coeffs$ for shifts $fred$. Obtaining the energy spectrum using the wavelet transform involves using not the squared wavelet coefficients, but their absolute values $abs(coeffs)$.

For a cardiac signal with noise, visual changes in wavelet scalograms are noticeable, which provide additional significant information for diagnosis and detection of anomalies and can be used for training a neural network (Figs. 9 and 10).

Despite the fact that changes in wavelet scalograms are visually easily identified, evidence-based medicine gives preference to numerical evaluation indicators. This is due to the fact that a significant share of expert subjectivity is present in visual evaluation.

To increase the efficiency of the method for analyzing artificial ECG signals, we use the technique that was used to process the most common signals [18, 29]. We study the correlation of hourly series of discrete wavelet coefficients of a cardiac signal using the example of a correlation matrix of time series compiled from a complete filtered data set using the wavelet packet filtering method ECG signal decomposition coefficients.

The open biosignal database PhysioNet [30] was used as the real medical data. PhysioNet is an open scientific platform that provides free access to a large amount of physiological and clinical data, tools for their analysis, and research resources. The platform contains various types of patient medical records, including electrocardiograms (ECGs), the data are anonymized and presented in formats convenient for processing. Among the most famous datasets hosted on PhysioNet is the MIT-BIH Arrhythmia Database. This database represents one of the first and most famous ECG datasets. Processing in accordance with the described methodology was applied to each file of the PhysioNet database.

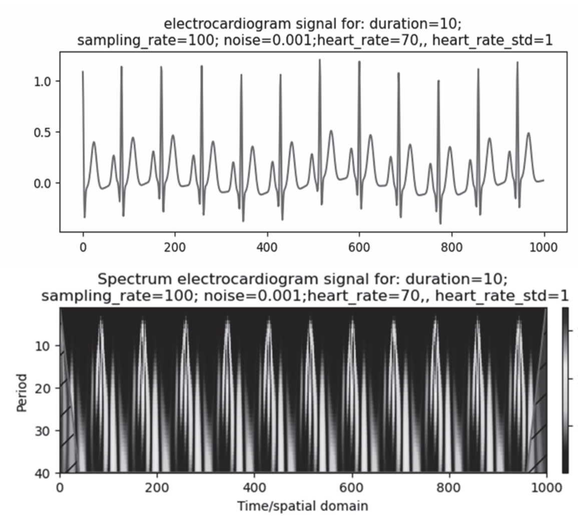

Fig. 9. Artificial ECG signal and signal spectrum with noise level $noise = 0.001$

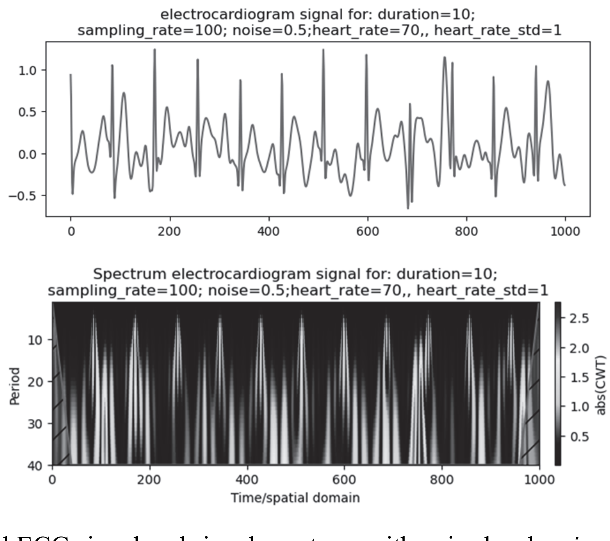

Fig. 10. Artificial ECG signal and signal spectrum with noise level $noise = 0.5$

A set of artificial cardiac signals is obtained by changing the parameters: duration (int) – desired recording duration in seconds; sample_rate (int) – desired sampling rate (in Hz, i.e. samples per second); length (int) – desired signal length (in samples); noise (float) – noise level (Laplace noise amplitude); heart_rate (int) – desired simulated heart rate (in beats per minute); heart_rate_std (int) – desired standard deviation of heart rate (beats per minute); method (str) – the model used to generate the signal. For a model based on Daubechies wavelets, this is “simple”. (Fig. 11).

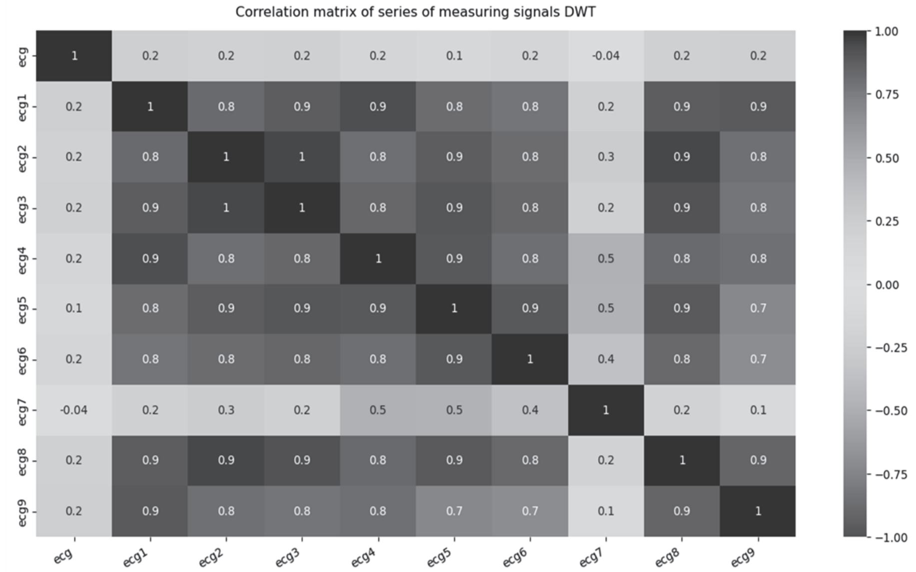

Fig. 11. Correlation matrix of functions from discrete spectra of artificial ECG signals

Using a correlation matrix makes it possible to identify groups of cardiac signals with similar influence of parameters. This significantly simplifies the task of creating artificial ECG signals, which are used as a test base.

For the matrix above (Fig. 11), we study the nature of the dependence of the entropy of signals on additively added noise (Fig. 12).

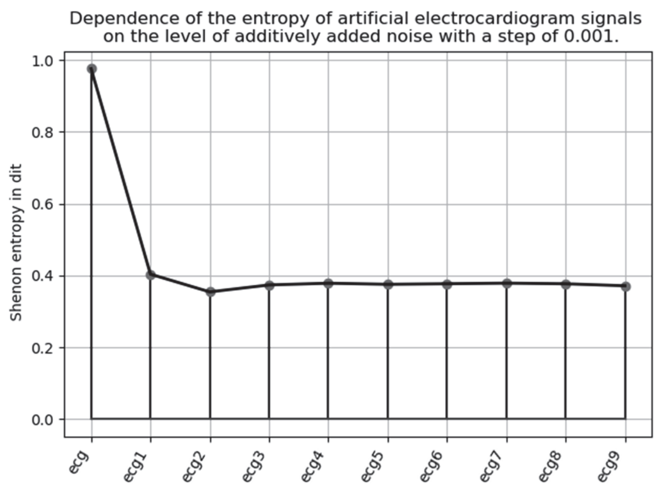

Fig. 12. Shannon entropy of artificial electrocardiogram signals

To classify ECG signals, we use Shannon entropy as a criterion, similar to the study [18]. In the study [18], signals are conventionally divided into simple and complex by comparing the numerical values of entropy.

A feature of ECG signal processing (Fig. 12) is that for a group of cardiac signals, as noise increases, their entropy remains constant. This feature is important when building ultra-precise neural networks using signal images.

To demonstrate the effectiveness of the developed signal generation model, a comparative analysis of the effectiveness of signal classification was performed using the KURIAS-ECG database [30]. KURIAS-ECG is a standardized database of 12-lead electrocardiograms with a common standard to facilitate cardiovascular research [31]. KURIAS-ECG Database consists of a CSV file and 20.000 waveform database files. The database comprises 20.000 ECG data from 13.862 patients. The average age of the patients is 58 years (±20), and the ratio of males to females is 56% and 44%, respectively. The ECG data consists of 10 classifications based on the Minnesota system, and each classification can be subdivided into statements provided by the ECG device. [29, 30].

The deep learning model used in well-known studies to verify the signal quality of the electrocardiogram database [29, 32] showed an average accuracy of 88.03% in classification for seven categories. The developed model for generating realistic shaped signals has the following accuracy indicators:

The Train Score is 1.0;

The Test Score is 0.9620253164556962.

The increase in the accuracy of the model classification is due to the fact that the work uses denoising of electrocardiogram signals using the packet wavelet filtering method (the approximation coefficients and detail coefficients are limited). Therefore, data preparation for CNN using sets of wavelet decomposition of ECG signals is more efficient (96.2%) compared to analogues.

CONCLUSIONS

A model has been developed for generating artificial electrocardiogram signals of realistic shape to create test signals. The difference between the models is the ability to control the duration, sampling frequency, noise level, and pulse rate using Ingrid Daubechies wavelets to simulate. The presence of a large list of cardiac signal parameters allows the model to be used to generate a wide range of ECG test signals. Using the parameters of artificial ECG signals, it is easy to prepare a DATASET for CNN training.

The synthesized ECG signals were studied using discrete wavelet analysis to study the influence of these parameters on the approximation and detail coefficients. It was found that the noise level has the most significant impact on detail factors. The number of signal peaks increases with increasing noise level.

For the first time, an optimal packet wavelet filtering algorithm for both detail coefficients and approximation coefficients of ECG signals was used to analyze ECG signals of artificial and natural origin. This approach made it possible to ensure a high degree of restoration of the cardiac signal to its original form and the lowest possible error in filtering ECG signals. Similar studies have been carried out for continuous wavelet transform with the generation of wavelet scalogram images. It has been shown that scalograms provide additional diagnostically significant information and changes in noise levels are visualized using scalograms.

Comparative analysis of the accuracy of the developed model for generating realistic signals with the indicators of known models showed that the developed model is more effective (96.2%) compared to analogues (88.03%). The increase in the accuracy of the model is due to the denoising of electrocardiogram signals by the method of packet wavelet filtering (limitation of approximation coefficients and detail coefficients). The effectiveness of the developed method is fully correlated with the correlation matrix of functions of discrete spectra of artificial ECG signals.

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ДОСЛІДЖЕННЯ Й ОБРОБЛЕННЯ ЕКГ-СИГНАЛІВ ЗА ДОПОМОГОЮ ДИСКРЕТНОГО ТА БЕЗПЕРЕРВНОГО ВЕЙВЛЕТ-АНАЛІЗУ / Ю.К. Тараненко, О.Ю. Олійник, Б.І. Мороз, Д.М. Мороз, В.В. Лопатін

Анотація. Присвячено аналізу сигналів електрокардіограм штучного походження реалістичної форми з можливістю керування тривалістю, частотою дискретизації, рівнем шуму та частотою імпульсів за допомогою вейвлетів Інгрід Добеші. Синтезовані сигнали досліджувалися за допомогою дискретного вейвлет-аналізу для вивчення впливу цих параметрів на коефіцієнти апроксимації та деталізації. Встановлено пріоритетний вплив шуму на коефіцієнти деталізації та залежність кількості піків сигналу від заданих параметрів. Уперше використано метод пакетної дискретної вейвлет-фільтрації коефіцієнтів деталізації та коефіцієнтів апроксимації. Це дозволило забезпечити високий ступінь відновлення сигналу до початкової форми. Аналогічні дослідження проводилися для безперервного вейвлет-перетворення з генерацією вейвлет-скалограмних зображень, які надають додаткову діагностично значущу інформацію. Результати, отримані у вигляді алгоритму, є перспективними для використання у ході аналізу сигналів радіолокаційних систем. Розроблено модель генерації сигналів реалістичної форми, яка є більш ефективною та перевищує середню точність (96,2 %) порівняно з аналогами (88,03 %). Ефективність розробленого методу повністю підтверджується кореляційною матрицею функцій дискретних спектрів штучних ЕКГ-сигналів.

Ключові слова: електрокардіограма (ЕКГ), вейвлет-перетворення, пакетна вейвлет-фільтрація, коефіцієнти апроксимації, коефіцієнти деталізації, пакетна фільтрація, класифікація.