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NEW WAY TO PROCESS SIGNALS DIGITALLY

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Abstract
Biomedical signal processing algorithms create a variety of opportunities to improve performance. This study proposed a new wavelet delta-function (WDF) method to effectively identify pathology from ECG signals. In this way, the delta function is determined for each value of the ECG signal. This is done through the WDF sum with a coefficient of 0, 1 and -1. The degree of difference between pathology and norm using data in the form of this vector allows you to make changes in diagnosis with greater accuracy than traditional methods. This is a new way to process EKG signals by converting graphical data into vectors. The new method has created a barcode-like image. Miocardial infarction (MI), one of the diseases of this cardiovascular system, has become more effective in real numbers of invisible peaks in the ECG. This makes it possible to identify the disease early and make a definitive diagnosis.
The model we propose is an effective way to analyze the ECG. The WDF model we have proposed can be used for early assessment of the disease when processing biomedical signals.

Keywords: EKG, Gauss wavelet, Biomedisina signallar, PhysioNet, Challenge 2011 Test Set B, algoritm, wavelet, delta-funksiya.

1. Introduction

It is known that every year, the World Health Organization (WHO) conducts research and publishes data on the main causes of deaths occurring around the world and in individual gods. Such research will help identify top-notch approaches to health care for each state.
According to WHO, the main causes of death worldwide today are cardiovascular disease, various infectious diseases and dangerous tumors. At the same time, the list of main causes of death in developed countries includes heart disease, stroke in the second place, dangerous lung tumors, pneumonia, bronchitis and asthma. In developing and low income countries, this list includes pneumonia, heart disease, HIV/AIDS, and stroke in the order of decline.
According to WHO worldwide, 56% of all deaths are caused by cardiovascular disease. In European countries, cardiovascular disease kills 4.3 million (48%) of the population a year.
Diseases of the cardiovascular system are supplemented by a person's lifestyle and existing risk factors. While many risk factors are controlled by lifestyle changes, some (arterial hypertension, dyslipidemia, and sugar levels) are corrected through medicamentosis.
Choosing a wavelet replacement mathematical apparatus to solve problems with the processing and interpretation of non-inpatient cardio signals is relevant to solve mathematical modeling issues using the final methods of wavelet analysis.

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The development of modern information communication technologies in the world and the implementation of them in various aspects of public administration, especially the creation of new effective algorithms for restoring signals, solving digital processing issues, the implementation of processing processes on the basis of wavelet replacement, and the discovery of optimal solutions are of particular importance. Therefore, with the help of computer technologies in developed countries, a number of initiatives are being undertaken to effectively diagnose cardiovascular disease, expand and facilitate the use of applications aimed at providing medical services. For example, great work is being done in the United States, Japan, Hermania, France, Great Britain, Russia, Italy, Australia, South Korea, the Chinese People's Republic of China, India, and Uzbekistan to diagnose and monitor myocardial infarction with apparatus-software tools based on wavelet replacement algorithms.

The level of study of the problem. To date, scientific and practical results have been obtained in terms of working with images, developing methods and algorithms for digital processing of electrocardiogram (EKG) signals, especially the development of a database of hardware-software tools for the diagnosis of myocardial infarction, mathematical modelling. For example, mathematical modification issues - G.I.Marchuk, YU. Analysis of N. Subbotin, V.A.Vasilnko, Wavelet: theoretical foundations and practical examples – Astafeva N. M., effective algorithms for replacing local discrete wavelets based on Haar – seen in the works of Copenhagen V.
The ECG has become a promising tool for achieving automatic detection of diseases using ecg associated with signal processing algorithms[1], [2]. To assess the feasibility and accuracy of these algorithms at the moment, it is usually based on existing databases such as the Physionet Database[3]. However, due to the exponential growth of data, the amount of available knowledge base is limited and not enough. Moreover, since commenting on the information is a task that takes a lot of time, hard work and money, it is impossible to get such large volumes of information with the labels. However, the way algorithms work can vary greatly under different clinical conditions, indicating the need for a large amount of explancerous data to ensure the effectiveness of the algorithms. In other words, even if multi-label data is not supported, and algorithms can work very well in this database, it may actually not be much of use. Therefore, the synthesis of accurate artificial ECG signals is of great importance to help researchers improve the performance of their algorithms in the field of ECG signal processing. By creating artificial and natural-looking specimens, researchers can achieve the goal of increasing the information, obtain multiple samples not included in the original database, and even obtain samples with unique characteristics. So far, there has been a lot of research on the synthesis of ECG signals using mathematical modeling. McSharry Vs. McSharry in 2003 [4] has proposed a two-step dynamic model for generating artificial ECG signals. First, they produced an internal time series, determining the spectral parameters and temporary parameters (average heart rate and standard deviation) of real R-R tacograph. Secondly, they formed motion equations, a three-dimensional (3-D) trajectory model and determined the highest points and heights of each heart rate to form the average morphology of ECGs. The waves P, Q, R, S and T are respectively represented by a set of gauss equations within this trajectory model and the EKG signal can be considered a sum of gauss equations of these waves. By adjusting the

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angle speed of the trajectory, the wave shape of the R-R interval could be changed. Li and Ma in 2005 [5] To model ECG signals, they proposed a data flow graph method based on the parts curve. The algorithm must model the P wave, the QRS wave and the T wave respectively and then synthesize the heart rate, which includes many parameters, thereby increasing the complexity of the algorithm. Sameni and so on. In 2007 [6] offered a 3-dimensional dynamic model that was a single dipole model for the heart and combined a linear model that indicates the transient movement and circulation of the heart dipoli. The model can be integrated into a multi-signal model. When compared to the one-signal model proposed by McSharry above, the multi-signal model proposed by Sameni avoids the problem of repeating parameters during multi-signal modeling. From the point of view of the dipole model of the heart, EKG signals in different directions are actually projection of the dipole vector of the heart to the arrow of the EKG writer electrode. The drawback of this algorithm is that the ECG signals repurposed from this model do not quite correspond to the actual ECG signals, especially at low frequencies such as the P wave. This indicates the limitations of a single-dipole model in the expression of low-frequency components of the ECG. Based on sameni's 3-dimensional dynamic model, Clifford et al. (2018). In 2010 year [7] Markov, who uses first-class chains to generate normal and abnormal heartbeats in the queue, and uses a transition matrix to express the possibility of passing between normal and abnormal heartbeats. Rooney et al. in 2013. [8] The ECG has proposed a signal fragment-based method to model signals, as a single ECG heartbeat can be treated as a sum of base functions. They tried a variety of groundbreaking features, such as guss model in style, polynomial spline models (including Bezier b and B-splines), and sinusoidal model. During their experiments, they found that the sinusoidal model and Bezier function did not meet local control requirements and that the B-spline function was able to provide the good local controls necessary for modeling. Traditional mathematical modeling methods have the following disadvantages:

While their model in the context of ECG morphology can produce very accurate heartbeats, these synthetic heartbeats are highly "standard." In other words, the morphology of each heartbeat in a synthetic ECG signal is very normal and basically the same.

Given that this model can be changed to produce abnormal heartbeat, such an adjustment can be complex and severe, since any abnormal heart rate is consistent with a certain set of equations.

Operators who use these types of models should have the expertise to make sure the accuracy, rationality and reliability of setting parameters.

In addition, the assessment of the quality of the signals produced is based primarily on visual observation with professional knowledge rather than scientific and objective methods.

On the other hand, the rapid development of in-depth teaching in previous years has led it to detect speech [9], image recognition [10], object detection [11] has successfully implemented biomedical science in many areas, such as [12]. Nowadays, many in-depth study-based EKG detection algorithms and signal processing algorithms have exceeded traditional methods in terms of accuracy. For example, in 2017, the stanford university professor Andrew Y. Ng group used a deep convocational network combined with a residual network to perform the detection of an algorithm-detection accuracy of an intimate or even identical signal arrhythmia signal[13]. In addition to the aforementioned discriminatory model, the generative model has also developed sharply in recent years.

In this article we have provided a WDF method of synthesis of ECG signals. To our knowledge, this is the first study to utilize in-depth learning to analyze ECG signals. Compared to traditional algorithms, the proposed approach has a number of advantages:

- incoming data * is read from the .txt file;
- The detection of EKG signals indicates the limit value of the proximity of wave functions;
- allows you to select a wavy function in the analysis;
- the amplitude value for wavy functions is entered;
- allows you to store the result and coefficients of the wave function.
- EcG signal tracking;
- Convert EKG values to numerical values in the form of binary vectors (0, 1 and -1) using the wave-delta function;
- show the value of the sum of coefficients in the specified range (interval or segment).

2. The mathematical basis of wavelet substitution

The most important means of analyzing stationary continuous signals is the Furye conversion of continuous time. Conversion coefficients are found by calculating the signal's point yield with complex indicators[14].

$$F(\omega) = \int_{-\infty}^{+\infty} f(x) e^{-i\omega x} dx, \quad (1)$$

Here - refers to the signal, and - its Fourier conversion.$f(x)F(\omega)$

x - time, - frequency. Reverse Furye conversion is determined by the expression belowω[15].

$$f(\omega) = \int_{-\infty}^{+\infty} F(x) e^{i\omega x} dx = F^{-1}(\omega). \quad (2)$$

Furye conversion provides information about the "level of presence" of the given frequency in the given signal spectrum. In practice, not all signals are motionless. Peak in time domain spreads across the entire frequency of its Fourier conversion[16].

2 Examples of Wavelet

Wavelets are most often formed on the basis of Deris of Gauss functions. The Gauss function and its opposite side:

$$\Psi_H(x) = (-1)^m \delta_t^m e^{\frac{-x^2}{2}}, \quad (3)$$

$$\widehat{\Psi}_H(x) = m(ik)^m e^{\frac{-x^2}{2}}. \quad (4)$$

The two most commonly used waves in practice are the Mexican hat and the Morlet wavelet (Fig. 1)[17]. Mexican shlyapasi - Gaussian funktsiyasining ikkinchi hosilasi,

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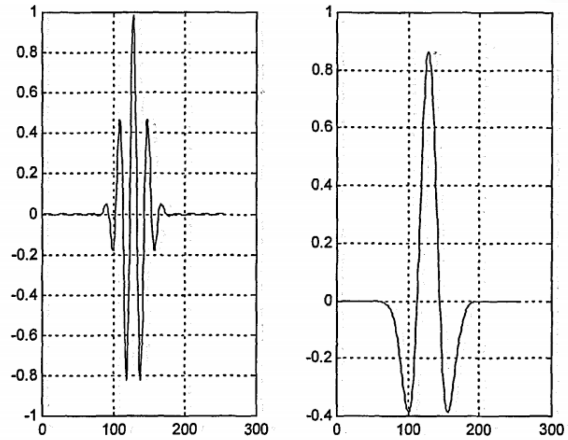
$$\Psi_H(x) = (1 - x^2)\delta_t^m e^{\frac{-x^2}{2}}, \quad (5)$$
$$\widehat{\Psi}_H(\omega) = \omega^2 e^{\omega^2}. \quad (6)$$



Picture. 1. Morlet and Mexican hat wavelet functions.

Time in the Abtsissa arrow, and the value of the function in the ordination.

It's a real wavelet that will be two zeros. It has a narrow energy spectrum.$(n = 0, 1)$

DOG waveleti (Difference of Gaussian) Gauss funktsiyasi asosida qurilgan.

$$\Psi_H(x) = e^{\frac{-e^2}{2}} - 0.5e^{\frac{-e^2}{8}} \quad (7)$$
$$\widehat{\Psi}_H(x) = \frac{1}{2\pi^{\frac{1}{2}}}(e^{\frac{-\tau^2}{2}} - e^{-2\tau^2} \quad (8)$$

Morlet wavelet is a Gauss function modulated by unit width[18](Figure 1).

$$\Psi_H(x) = e^{t\omega_0 x} - e^{\frac{-x^2}{2\sigma_0^2}}, \quad (9)$$
$$\widehat{\Psi}_H(x) = e^{\frac{-[(\omega-\omega_2)\sigma_0]^2}{2}}. \quad (10)$$

The first expression does not satisfy the conditions of individual acceptance, therefore, a correction will be needed. However, for a large enough (usually) one, this correction is insignificant in numbers. Without correction, (9) the Gabor function is also the most common function used.$\omega_0\omega_0 \Rightarrow 5.5F_\Psi(\omega, b)$[19]

$$\Psi_H(x) = \frac{e^{i\Omega(t-t_0)-i\theta}e^{\frac{-(t-t_0)}{2\sigma^2}}}{\sigma(2\pi)^{0.5}}. \quad (11)$$

Gabor funktsiyasining kengayishi - this is sinusoidlarning modulyatsiyalangan bo'laklaridagi kengayish.

The morlet wavelet is complex, so the corresponding replacement is also complex and the phase and module can be considered separately. It turned out that the replacement phase is a component that determines the algorithm for determining signal properties.$F_\Psi(a, b)$

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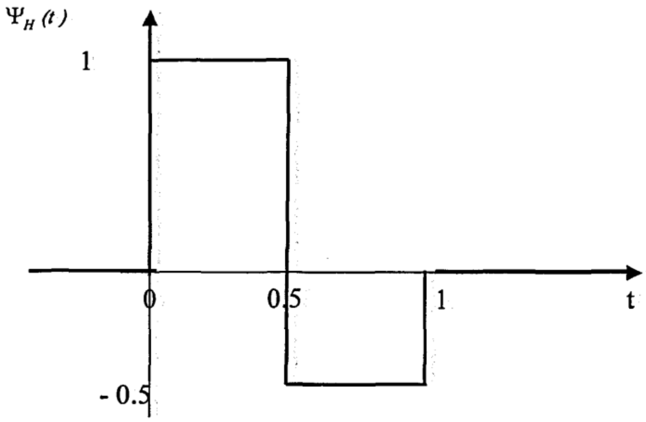
The HAAR (Haar) wavelet is an example of the simplest orthogonal discrete wave that creates an orthopaedic basis. (Figure 2).

$$\Psi_H(t) = \begin{cases} 1, & 0 \le t \le \frac{1}{2}; \\ -\frac{1}{2}, & \frac{1}{2} \le t < 1; \\ 0, & t < 0, t \ge 1. \end{cases}$$



Picture. 2. Haar wavelet function.

Time in the Abtsissasi arrow, and the value of the function in the ordination.
The disadvantages of this wavelet are the incomplete - the sharp edges in the gap, as a result of which (decreased) - there will be no gap "tails", as well as the symmetry of the shape.$tk^{-1}k$

3. Selection of delta functions for the wavelet delta-function algorithm

Wavelet replacement has a lot of wavelet functions (base functions). A common feature of these functions is that they are defined at a certain interval.
Wavelet replacement is well adapted for non-stationary signal analysis, so it has become a powerful alternative to conventional spectral and correlational analysis. Most biomedicine signals are non stationary and have narrow localized properties and to analyze these signals, you need a method that provides good accuracy both in the frequency and at the time. Wavelet methods are used to identify and recognize the basic diagnostic properties of biomedical signals, as well as to compress images with minimal loss of diagnostic data.
For processing, we primarily use non-stationary processing of biomedical signals and self-proven delta functions [20].
Now let's look at the functions of this wavelet. We use the following wavelet functions:
3.2-rasmda hair wavelet (hair), mhat (meksika shapkasi), morl (morlet) va gauss (gauss) funktsiyalari grafigi tasvirlangan.

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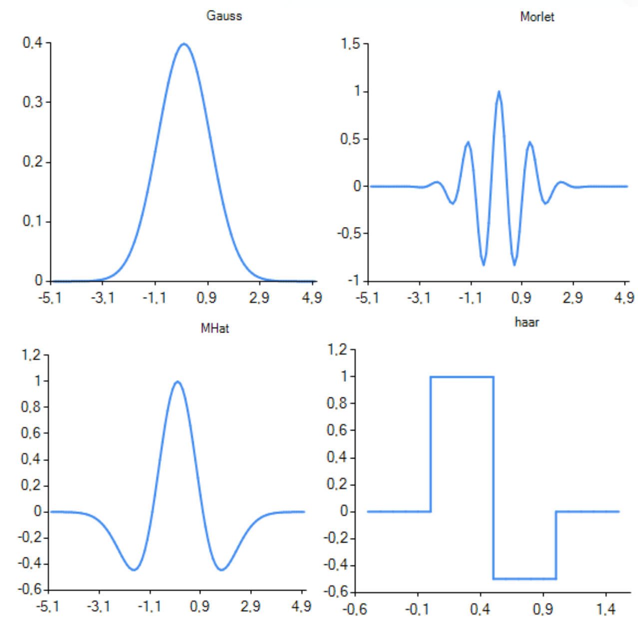

3.2-rasm. Wavelet replaces various wavelet functions, while time in a horizontal arrow and amplitude in a vertical arrow, that is, the height of the function.

Let's see the Morlet wavelet function (morl) for the algorithm for determining coefficients in the binary vectro view. It is recommended for processing non-stationary signals of various shapes and contains the largest information about the signal being studied.

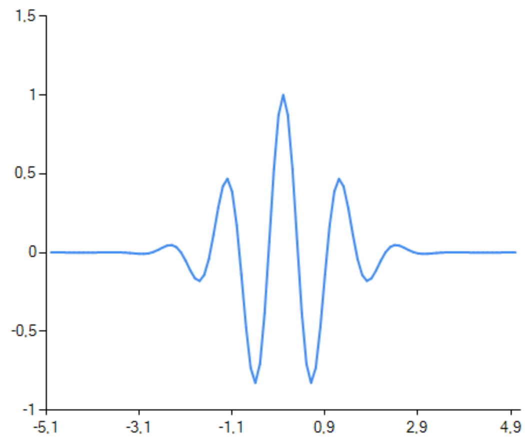

Figure 3.3 is a graph of morlet function, time in a horizontal arrow, and the value of the function in a vertical arrow.

In this case, the Morlet function, which is included in the computing algorithm, has the following form:

$$f(t) = ae^{\frac{-t^2}{2s}}\cos(5t)$$

Another function is the sin xaara function (1.6-rasm). This is how you can

$$\psi(x) = a\left(\frac{\sin(x-b)}{x-b}\right)^s$$

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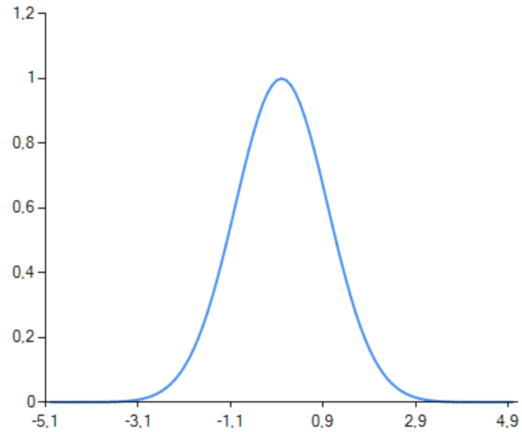
In this case, *the* function A amplitude is balancing, the b-shift parameter, the s-sigma-function width. This fulfills the following condition

$$\psi(x) = \begin{cases} 0, agar\ x \neq 0 \\ \infty, agar\ x = 0 \end{cases}$$



3.4-rasm. Sin xaara function graph. And the value of function in time ordination in the Abstsissa arrow.

Jadval 3.1

Parameter values included in the calculation algorithm for wavelet functions

Wavelet funktsiya	**eps-chegaraviy qiymat**	**A-amplitude**	**s-sigma**	**t-time**
Gauss	0,03	0,02	0,012	0,002
Morlet	0,03	0,02	0,00012	0,002
Mhat	0,03	0,02	10100	0,002
Sin her	0,03	0,02	11000	0,002

The wavelet of these cardio signals – with the delta algorithm, provides static parameter values given to various wavelet functions for the processing of EKG signals (see table 3.1).

4. Wavelet delta-function algorithm

The approach offered to ECG processing is based on continuous variation of wavelets (WUO'). Variations in wavelets on different scales characterize the time characteristics of the signal in a different frequency range.

In a traditional way, coefficients are taken differently to describe the ECG.k_j

$$n * \delta(x, x_0) \approx \sum_{i=-\frac{n}{2}}^{\frac{n}{2}} \delta(\sigma, x, x_{0i})$$

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Above we consider the possibility of replacement in the formula and achieve this by selecting the parameter.σ

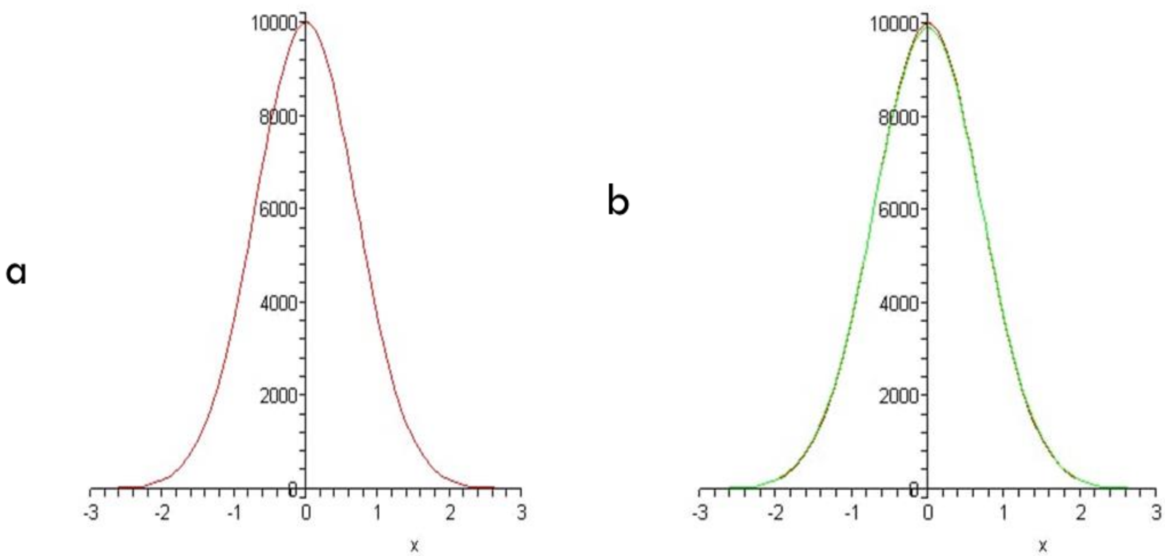

Figure 3.5. (a) and (b) graphics.$n * \delta(x, x_0) \sum_{i=-n/2}^{n/2} \delta(\sigma, x, x_{0i})$

Given the ability to record EKG signals with wavelet replacement, according to an error identified by the average quadtatic separation method

$$\Delta_j = \left| n * \delta(x_j, x_0) - \sum_{i=-n/2}^{n/2} \delta(\sigma, x_j, x_{0i}) \right|$$

from to the following view

$$\bar{\Delta} = \sum_{j}^{k} \frac{\Delta_j}{k}$$

From this - the average value, the number of k-points, , j=1.2,...,k, – the difference between the value of the two functions. $\bar{\Delta} k \in N \Delta_j$

$$\sum_{j=1}^{n} \left| \Delta_j^2 - (\bar{\Delta}_j)^2 \right| < \varepsilon \qquad (3.1)$$

In this case, -boundary value.ε

(3.1) Recognizing the implementation of the condition, the coefficient wavelet-delta function was deemed worthy of implementation.

Based on the above literature analysis (see chapter 1), we use the following basic formula to replace wavelets.

$$\mathrm{X}(t) = \frac{1}{a} \int_{-\infty}^{\infty} x(t)\, \psi\left(\frac{t - t_0}{a}\right) dt \qquad (3.2)$$

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bunda - wavelet funktsiyasi, - rostlash parameters, – o'tish parameters.$\psi(t) a t_0$
The following formula is used for digital processing

$$\mathrm{X}(t) = \sum_{i=1}^{\infty} x(n_i)\frac{1}{a}\psi\left(\frac{t-t_{0i}}{a}\right) \qquad (3.3)$$

The calculation of the alarm can be carried out according to the following formula:

$$\mathrm{X}(t) = \sum_{k=1}^{\infty}\sum_{i=1}^{\infty} x(n_i)\frac{1}{a}\psi\left(\frac{t_k-t_{0i}}{a}\right) \qquad (3.4)$$

We tried multiple prototype wavelets to find the optimal wavelet to our algorithm. [21],[22] As a delta function, an asymmetric function of the following forms was used:

$$\psi(t,t_0,\omega) = \frac{1}{\omega} exp\left(\frac{(t-t_0)}{\omega} - exp\left(\frac{t-t_0}{\omega}\right)\right) \qquad (3.5)$$

If (3.5) the exponential function is approximated to 2 order, we will get the following formula.

$$\psi(t,t_0,\omega) = \frac{1}{\omega} exp\left(\frac{(t-t_0)}{\omega} - \left(1 + \frac{(t-t_0)}{\omega} + \frac{(t-t_0)^2}{2\omega^2}\right)\right)$$

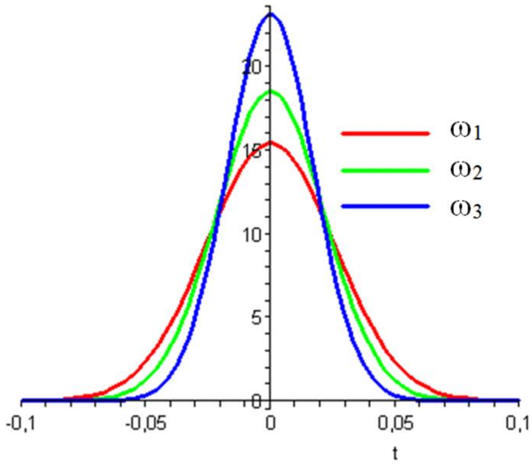
Once the expression is simplified and normalized, we get the Gauss distribution:

$$\psi(t,t_0,\omega) = \frac{1}{\sqrt{2\pi}\omega} exp\left(-\frac{(t-t_0)^2}{2\omega^2}\right) \qquad (3.6)$$

Figure 3.6 shows the graphs according to the formula for different values (3.6).ω
Then timely calculation of the continuous signal is carried out according to the following formula:

$$\mathrm{X}(t) = \sum_{k=1}^{M}\sum_{i=1}^{N} x(n_i)\frac{1}{\sqrt{2\pi}\omega} exp\left(-\frac{(t_k-t_{0i})^2}{2\omega^2}\right) \qquad (3.7)$$

In this case, the value M is selected taking into account the issue. Based on the values in the time interval studied. The value of N is determined in such a way that as it increases, it becomes insignificant. This can be considered a limited number.$(t_k - t_{0i})^2$



3.6-rasm. Graphs by formula for different (3.6).ω

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It's and [22] The following (3.6) formula allows you to think. At the same time, we have the task of determining the coefficients ahead of us. It is important to note that we are now looking for coefficients 0, 1 and -1 in a cycle cycle of the ongoing process$x(n_i)$[19][23][24][25][17][26].

From the foregoing, the wavelet replacement function appeared as follows:

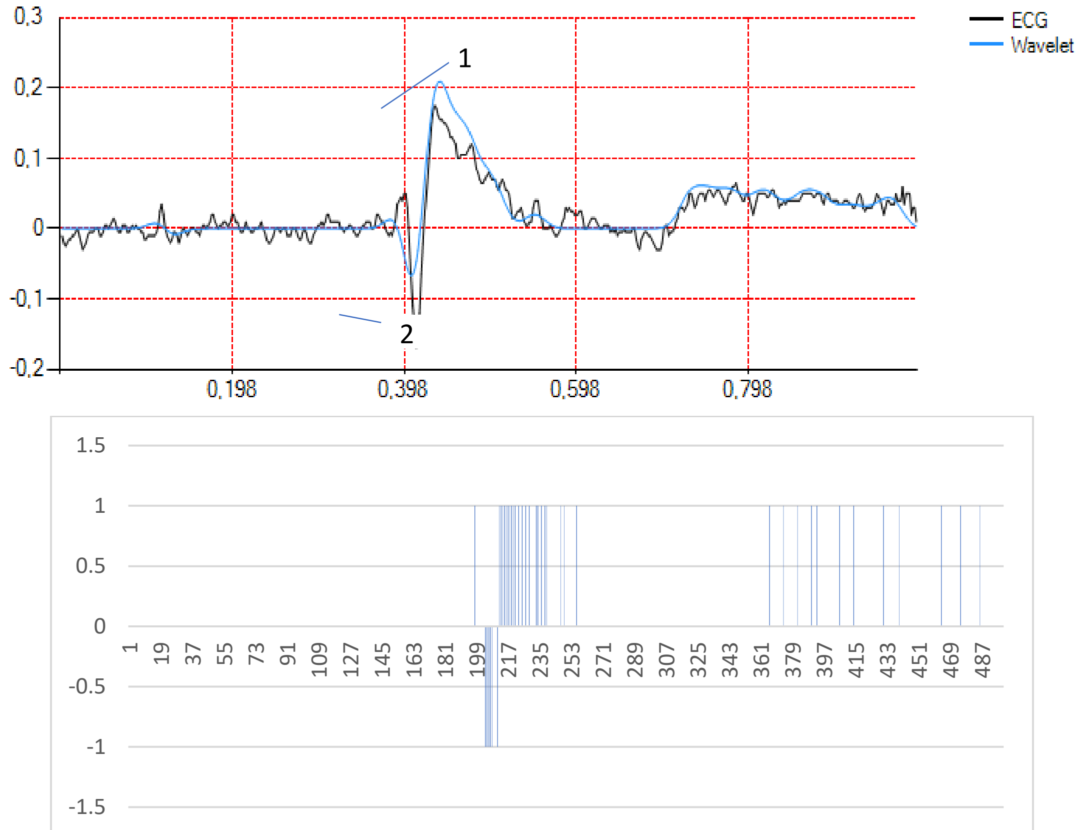
$$S = \sum_{i=0}^{n} \sum_{j=0}^{n} k_j A e^{-\frac{(x_i - x_j)^2}{2\sigma^2}} \qquad (3.8)$$

In this case - a sum of delta functions, a coefficient of k - 0, 1 and -1, -represents the height of the parameter and -amplitude function that meets the width of the function.$Sn \in N\sigma A$

We find the coefficients in the formula (3.8) when modeling EKG signals in binary form (consisting of 0, 1 and -1).k_j

a

b



3.8-rasm (a) EKG signal -2 line and delta function sum (wavelet) -1 line, (b) EKG, given in the form of barcodes

Vector View Data

After the calculations made, we received a curve describing the ECG signals. This was done by selecting a number of coefficients, which represents a dimensional binary vector, i.e. a coordinated vector with numbers -1, 0 and 1, which are the main indicators in which coefficients can store valuable data. Data

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processing is determined by the fact that there is a small wave at the time point, the presence of a coefficient corresponding to the unit. This allows the resulting binary vector to be reflected in the form of barcodes, where the presence of a vertical line line on the time scale means 1, and the space is 0 (see figure 3.8 b). At the time of diagnosis, it is enough to determine whether there are or not lines in the time section. The acquisition of a binaries vector depends on the choice of wavelet or delta function, in this case (3.7) the formula is the Gauss function, which of course depends on the detection algorithm.$Nx(n_i)Nt_it_i$

Conclusion

A new WDF method has been created for ECG signals. With this method, the wavelet coefficients of the EKG signal are obtained in the form of 0, 1 and -1. With the help of this vector data, the detection rate of difference between pathology and the norm was improved. A new method of processing EKG signals has been developed by converting graphical data into vectors. The new method has created a barcode-like image. The patient was also offered a method of effective diagnosis using the resulting image.

With the help of coefficients, invisible peaks in the ECG graph of cardiovascular disease can be seen more effectively in certain numbers. This made it possible to detect the disease early and make a definitive diagnosis.

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