

## Algorithm for Preprocessing Electrocardiosignal for a Wireless Holter Monitoring System

Yuliya Gerasimova<sup>1</sup>, Fatimah Sidi<sup>2</sup>, Lili Nurliyana Abdullah<sup>3</sup>, Victor Ivel<sup>1</sup>, and Sayat Moldakhmetov<sup>1\*</sup>

<sup>1</sup>*Department of Energetic and Radioelectronics, Faculty of Engineering and Digital Technology, M. Kozybayev North-Kazakhstan University, 150000 Petropavl, Kazakhstan*

<sup>2</sup>*Computer Science Department, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia*

<sup>3</sup>*Department of Multimedia, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia*

### ABSTRACT

The article describes the principles of developing a preprocessing algorithm for electro cardio signals in an in-house wireless automated Holter cardiac activity monitoring system. The system stands out for lower energy consumption due to the compression and processing of transmitted information. The article's authors propose a wireless electro cardio signal transmission method based on energy-saving Wi-Fi technologies for transmitting electro cardio signals. The article also includes a step-by-step electro cardio signal filtering technique, which lies in an algorithm combining wavelet compression and low-frequency filtering and an algorithm for high-frequency and neural network filtering of transmitted electro cardio signals, ensuring high reliability of the transmitted electrocardiographic (ECG) information. The authors developed a Holter monitoring system model, which includes real-time MATLAB system packages, the PhysioBank's Automated Teller Machine electro cardio signal database, and an external wireless subsystem for transmitting ECG information. The authors also present a real-virtual complex for setting up and implementing the algorithm of the developed system, providing a wide range of software and hardware tools, including specialised MATLAB

system packages for setting up, debugging, and optimising operating modes. The analysis of the obtained time diagrammes showed no interferences after the signal reception, transmission, and processing, and the valuable signal increased fourfold. This electro cardio signal processing enhances the quality of ECG identification and interpretation. The developed wavelet-based algorithm provides an ECG data compression ratio of about 8:1, ensuring the

### ARTICLE INFO

#### Article history:

Received: 08 April 2025

Accepted: 24 September 2025

Published: 25 February 2026

DOI: <https://doi.org/10.47836/pjst.34.1.25>

#### E-mail addresses:

yugerasimova@ku.edu.kz (Yuliya Gerasimova)

fatimah@upm.edu.my (Fatimah Sidi)

liyana@upm.edu.my (Lili Nurliyana Abdullah)

vivel@ku.edu.kz (Victor Ivel)

ssmoldahmetov@ku.edu.kz (Sayat Moldakhmetov)

\* Corresponding author

preservation of diagnostically important signal features. The proposed methods and algorithms ensure high-quality, multi-day wireless transmission of ECG signals with low energy consumption.

*Keywords:* Signal preprocessing, electro cardio signal, electrocardiograph, Holter monitoring, wavelet, Wi-Fi transceiver, real-time signal processing

---

## INTRODUCTION

Holter daily monitoring is a diagnostic procedure in electrocardiography that includes recording the electrical heart activity using a portable device for 24 hours or more during the patient's free activity. Decoding and interpretation are often performed offline on special decoders. This type of ECG monitoring is used to diagnose heart rhythm and conduction disorders that cannot be detected by the standard ECG recording (Cai et al., 2019).

Typically, Holter monitoring involves recording ECG onto an autonomous storage device, such as flash memory, over a long period (Khong et al., 2021). However, the recorded data, in this case, becomes available and can be analysed only after the registration is complete. Therefore, wireless ECG transmission from patients directly to a computer has recently been increasingly used for continuous ECG monitoring of patients and further interpretation (decoding) of ECG in real-time (Sahoo et al., 2022). Here, a general server in a cardio centre or a separate minicomputer at home can be used as the computer. This system allows for promptly informing the patient and/or doctor about deviations in cardiac activity.

Identifying ECG elements involves determining the boundaries of specific sections, amplitudes, and durations of ECG waves, as well as the morphological features of all ECG elements, using modern methods of automated electro cardio signal (ECS) processing (Shaikh et al., 2022; Setiawidayat, 2023). Calculating the time and amplitude parameters of specific ECG fragments requires preliminary ECS processing, which includes low- and high-frequency filtering of ECS, elimination of ECG baseline drift, and software compression of the transmitted ECG data.

Although the theory of detecting ECG signal features and estimating its parameters is quite well developed, applying several classical solutions to their study takes time and effort. This is primarily due to the significant degree of a priori uncertainty in the properties of ECG signals and noise, which are determined by the individual characteristics of patients. Sources of noise can include the electrical activity of tissues, such as muscle tremors, interference from equipment, such as 50 (60) Hz noise, and slow changes in electrode polarisation potential because of the patient's forced breathing and coughing, which can cause baseline drift (Singh et al., 2017). Therefore, one of the requirements for any automated electrocardiography systems, including Holter monitoring systems, is to provide high-quality ECG data. Thus, the problem of ensuring high-quality preliminary processing of the measured electro cardio signal becomes relevant.

## LITERATURE ANALYSIS AND PROBLEM STATEMENT

The preliminary processing of the measured electro cardio signal and its preparation for wireless transmission to a computer diagnostic system can be divided into several stages (Ivel et al., 2019). The main stages include packet packing and compression of the transmitted ECG data, Wi-Fi data transmission, Wi-Fi ECG data reception, restoration and low-frequency filtering of the received ECG data, high-frequency filtering (elimination of baseline drift), band-stop, and neural network filtering.

One of the primary quality indicators of the wireless Holter ECG monitoring system performance is the speed of ECG data transmission and noise resistance. Wireless transceivers maintaining all necessary characteristics while having relatively low power consumption are particularly interesting. Leading devices in this class include transceivers based on ESP32 chips (Gerasimova et al., 2024). ESP32-based Wi-Fi modules provide extended range, larger memory, dual-core processing capabilities, improved support for maintaining stable wireless connections with low power consumption, making them particularly suitable for wearable biomedical devices.

Given this, there is a need to select or develop an efficient algorithm for compressing the transmitted signal's volume and subsequent filtering, allowing the electro cardio signal to be restored for proper interpretation.

The wavelet transformation procedure is interesting in this context due to its advantages. The wavelet transformation application successfully resulted in the processing of noisy electro cardio signals (Kumar et al., 2021; Malik et al., 2023). Since some noise sources contain frequency components within the ECG spectrum, removing them using standard filtering is quite challenging. In such cases, signal noise reduction is possible using wavelet de-noising. In studies (Asif et al., 2023; Jain et al., 2024), wavelet transformation is used for analysis to detect various pathologies. However, these works do not consider its use for data compression for subsequent transmission. Chuiko et al. (2021) presented a new algorithm and filter based on wavelet transformation for analysing and interpreting signals, though the focuss here was primarily on electromyogram signals, although electro cardio signals are quite similar in some parameters.

In some studies (Lin et al., 2024; Mohonta et al., 2022), the authors merely mention the application of DWT or CWT without providing a detailed description of the algorithm and wavelet transform parameters. Similarly, in Wang et al. (2021) and Maleki et al. (2024), the transform is used only as a feature extraction step, while key algorithmic parameters remain undisclosed. The absence of detailed descriptions of the wavelet transform algorithm complicates reproducibility of results and objective comparison with other methods.

This work presents an efficient algorithm for compressing and filtering electro cardio signals. This algorithm not only improves the quality of the transmitted information but also significantly reduces its volume. Compressing the transmitted data also contributes

to system energy conservation, which is crucial for a device worn by a patient throughout the day.

## **AIM AND OBJECTIVES OF THE RESEARCH**

This work aims to develop principles for the preliminary processing of the electro cardio signal that ensures their quality interpretation with sufficient compression of the transmitted ECG data and in the presence of broadband noise for wireless Holter monitoring systems. Alongside the application of energy-efficient wireless transceivers, developing an efficient algorithm for ECG data compression will contribute to the system's energy conservation. This will reduce the mass and size of the power element of the portable electro cardio diagnostic device when creating the system.

To achieve this aim, the following objectives were set:

- to develop and study an algorithm for the ECG data transmission and processing using wavelet transformation for the Holter monitoring system; and
- to develop a filter for the electro cardio signal transmission and processing.

## **MATERIALS AND METHODS**

The Holter monitoring system is based on the structure described in Gerasimova et al. (2025), the schematic of which is shown in Figure 1, and includes the following components:

- lead cable with disposable electrodes;
- amplifier module based on the AD8232 chip;
- ADuCM350 microcontroller (Li et al., 2019), built on the ARM Cortex™-M3 core from Analog Devices;
- Wi-Fi transmitter ESP32, connected to the microcontroller via the I2C interface;
- 18650 Lithium Battery Shield for powering the autonomous part of the system; and
- Wi-Fi receiver (identical to the transmitter), connected to a personal computer via the Arduino DUE.

The programme for the ADuCM350 microcontroller and the Wi-Fi transmitter microcontroller was written in C++. The personal computer is intended to receive and interpret ECG data on the receiving side, visualise the results of automated diagnostics, and transmit them to a printer for presenting a preliminary report.

The feature of the ECS measurement and wireless transmission algorithm, shown in Figure 2, is the division of system resources to execute the programme between two processors. The primary function of the ESP32 transmitter processor is to form and transmit the data array to the receiving side. The limited resources of this processor

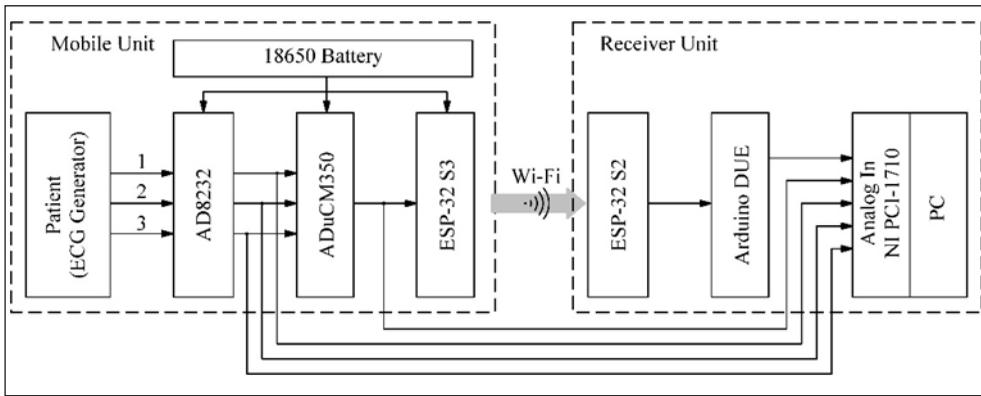


Figure 1. Functional diagramme of Holter monitoring system

do not allow for parallel computations. Therefore, a second processor has been added to the Wi-Fi transmission device, which operates in ECS recording and preliminary processing mode. At the same time, the transmitter transmits data to the receiving side. The second processor is the ADuCM350 microcontroller, whose software and hardware capabilities allow implementing programmes with parallel execution of various operations, including the discrete wavelet transform (DWT) algorithm.

The algorithm for the transmitting part of the system starts with measuring the ECG signal in one lead and forming an array  $M(i)$  in the ADuCM350 microcontroller. This array includes about 21,600 measurements with a period between measurements of 1 ms or a frequency of 1 kHz. This number of measurements corresponds, on average, to twenty-one cardiac cycles. The obtained data array is then subjected to multilevel one-dimensional wavelet decomposition (MOWD) (Slyusar et al., 2021).

As a result, a vector  $C$  containing approximation and detail coefficients and a vector  $L$  fixing the coefficient junction numbers are formed (Harang et al., 2012), while the detail coefficients are zeroed at a certain level  $N$ . The programme for creating the

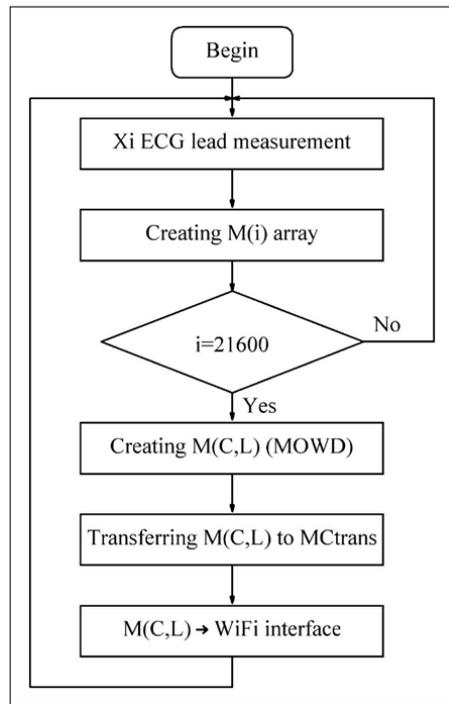


Figure 2. ECG transmission algorithm for the Holter monitoring system

array  $M(C, L)$  from vectors  $C$  and  $L$  is implemented in the Tensilica L106 Wi-Fi transmitter processor ( $MC_{tr}$ ). It should be noted that the two microcontrollers operate independently of each other. Simultaneously with the Wi-Fi transmission of ECG data, the ADuCM350 microcontroller continues collecting data from the patient. At the same time, the wavelet decomposition and the obtaining of detail coefficients  $C$  and  $L$  are performed. Thus, a parallel operation effect for processing and transmitting data is created.

Next, the ECG data packet is transmitted via the Wi-Fi interface to the receiving side, where the final recipient, a personal computer, performs wavelet reconstruction: it recreates the array  $M(i)$  of ECG data based on the coefficients  $C$  and  $L$ . Figure 3 presents the algorithm for the receiving part of the system.

Thus, ECG data is transmitted over the Wi-Fi network not as direct ECG signals but as vectors  $C$  and  $L$ . Zeroing specific detail coefficients of vector  $C$  leads to significant compression of the transmitted information and suppression of high-frequency noise in the reconstructed ECG signal. Consequently, wavelet transformation technology in Wi-Fi information transmission improves the quality of transmitted ECG data and reduces the system's power consumption. The main task of the algorithm presented in Figure 3 is the preliminary processing of the received ECG data.

**RESULTS OF THE ECG TRANSMISSION AND PROCESSING ALGORITHM DEVELOPMENT**

The algorithm is implemented in the MATLAB environment. The pre-obtained packet of  $C$  and  $L$  vectors is recorded in the MATLAB Workspace, and then, after the inverse wavelet transformation, the recorded ECG array is filtered step-by-step.

Noteworthy is the band stop filtering placement on the system's receiving side. However, filtering the ECG signal from 50 Hz interference on the transmitting side would be logical. This is because the ADuCM350 microcontroller lacks the resources for simultaneous discrete wavelet transformation and high-quality selective filtering of the ECG.

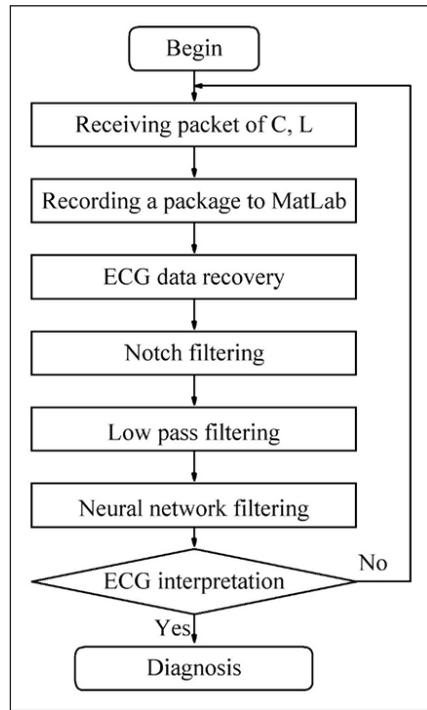


Figure 3. Algorithm for receiving and processing ECG data for the Holter monitoring system

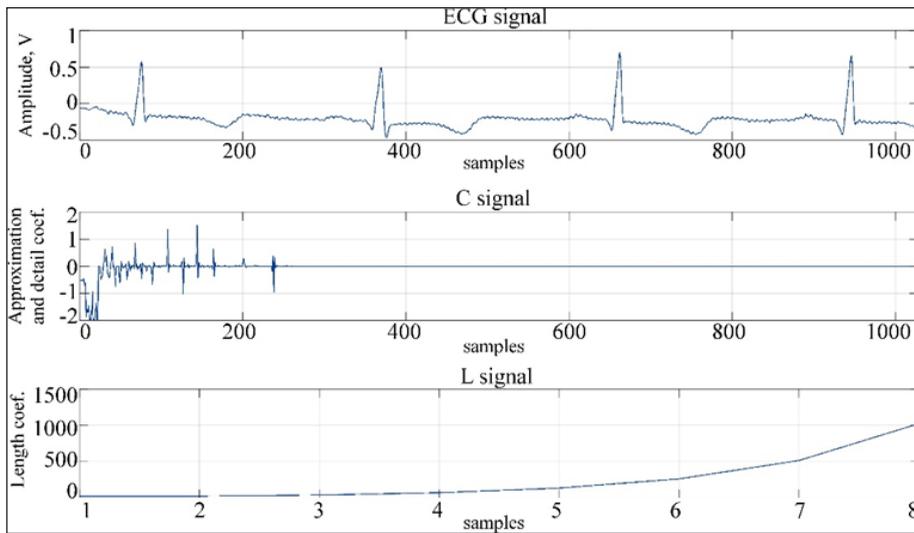


Figure 4. Graphs of the original ECG signal and detail coefficient vectors C and L

It should be noted that the entire Holter ECG monitoring process is continuous except for the initial time delay for the first measurement of the ECG data array, which is approximately 21 seconds.

Semi-realistic modelling was used for debugging and adjusting the parameters of the wireless ECG transmission system, as well as testing the ECG analysis algorithms and various operating modes of the system. This principle involves using computer models alongside real system components. The developed model contains real Wi-Fi transceivers, a router, computer software models of the direct and inverse wavelet transformation systems, and ECG signals from the PhysioBank archive database. Special software packages and hardware are used to implement the interface between the real components and the computer models of the Holter monitoring system.

The PhysioBank's Automated Teller Machine (PhysioBank ATM) archive database is a web resource containing well-described ECG signals and corresponding open-source software for the biomedical research community (Benmessaoud et al., 2023). The application to the ECG database presents the technology for transferring ECG copies to the MATLAB environment. This technology can record any copy of the ECG signal in the MATLAB workspace. In this case, it is an ECG signal variable in the 1x21600 double format. It is advisable to use the "wavedec" function to implement multilevel one-dimensional wavelet decomposition, and for clarity, the signal will be presented in the range of 1:1024 (number of samples).

Figure 4 shows the original ECG signal of vector C (2700 sample length) and vector L (8 sample length). The compression ratio (CR) is defined as:

$$CR = \frac{N_{orig}}{N_{comp}} \tag{1}$$

where  $N_{orig}$  is the number of samples in the original signal (21600), and  $N_{comp}$  is the number of samples in the compressed representation (2708).

Thus, the transmitted data array, i.e., vectors C and L, is approximately eight times smaller than the original ECG signal array, while preserving diagnostically significant information.

The “waverec” function is used on the receiving side for multilevel one-dimensional wavelet reconstruction. For clarity, the signal is also presented in the range of 1:1024 Figure 5.

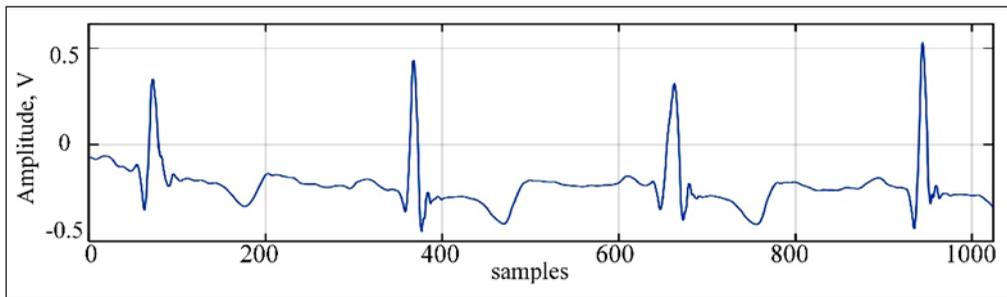


Figure 5. Graph of the reconstructed ECG signal

Figure 5 demonstrates that the reconstructed ECG signal is free from the high-frequency noise present in the original signal.

Simulink packages, Simulink Desktop Real-Time, the multifunctional PCI-1710HG input-output board, and the ADAM-3968 switch with connecting cable are used for the hardware implementation of the described process for transmitting and receiving arrays of vectors C and L using Wi-Fi technology. Figure 6a shows the Simulink model ( $SM_{out}$ ) for transmitting vectors C and L, recorded in the Workspace, to the output contacts of the PCI-1710HG board (Analog Output). Figure 6b shows the Simulink model ( $SM_{in}$ ) for receiving vectors C and L and recording them in the Workspace.

Since the output signal of the PCI-1710HG board has a positive polarity, a constant component of “0.5\_V” (Constant) is included in the circuit (Figure 6a) to eliminate the harmful component. To restore the input signal, a constant component of “-0.5\_V” is added to the circuit (Figure 6b).

A similar procedure is needed for an ECG signal mixed with a 50 Hz sinusoidal noise. For this purpose, a Simulink model ESC\_sin.slx was created Figure 7.

Figure 8 presents the results of forward and inverse wavelet transformation of an ECG signal mixed with 50 Hz noise. To determine the harmonic with the maximum amplitude in

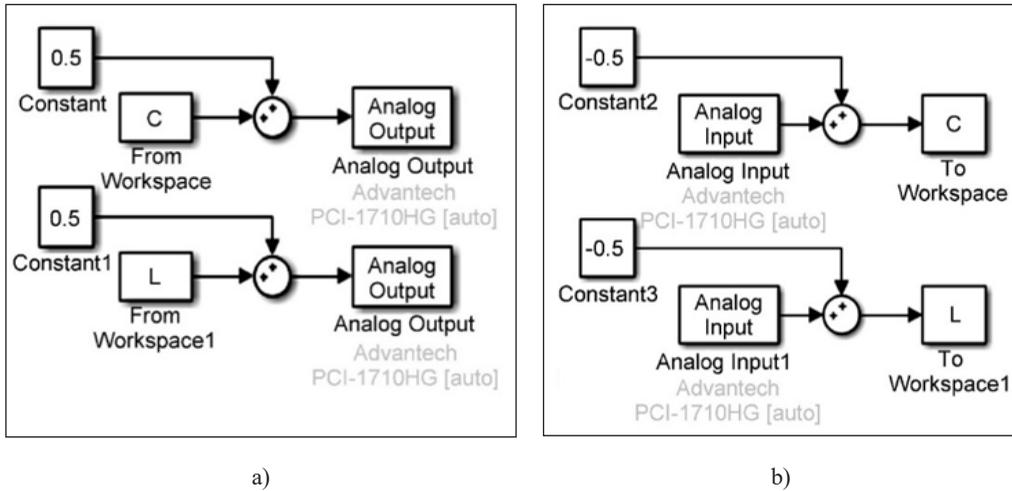


Figure 6. Simulink models for data input and output using PCI-1710HG board: a – Transmission of Vectors C and L; b – Reception of Vectors C and L

the spectrum of the restored ECSsinV signal, the magnitude spectrum for the 1024-point signal sequence must be computed and constructed.

The spectral density magnitude graph shows that two harmonics with the following frequencies were formed after wavelet transformations instead of a single 50 Hz harmonic:

$$f_1 = \frac{k_1 f_D}{N} = \frac{k_1}{NT_D}; f_2 = \frac{k_2}{NT_D}, \quad [2]$$

where:

$k_1$  and  $k_2$  are discrete normalised frequencies of the harmonics;

$f_D$  is the decimation frequency;

$T_D$  is the decimation period or sampling time;

$N$  is the length of the sequence (signal).

Numerical values:  $k_1 = 113$ ,  $k_2 = 146$ ;  $T_D = 0.0028$  s;  $N = 1024$ .

After substituting the values into the formula, the frequencies were determined as  $f_1=39.4$  Hz and  $f_2=50.9$  Hz. This noise with two harmonics needs to be removed through filtering.

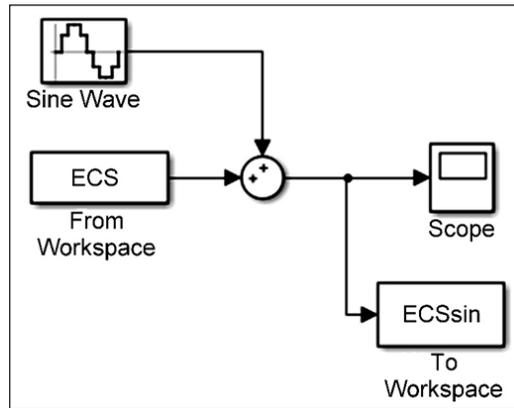


Figure 7. Simulink model for recording ECG signal with 50 Hz noise

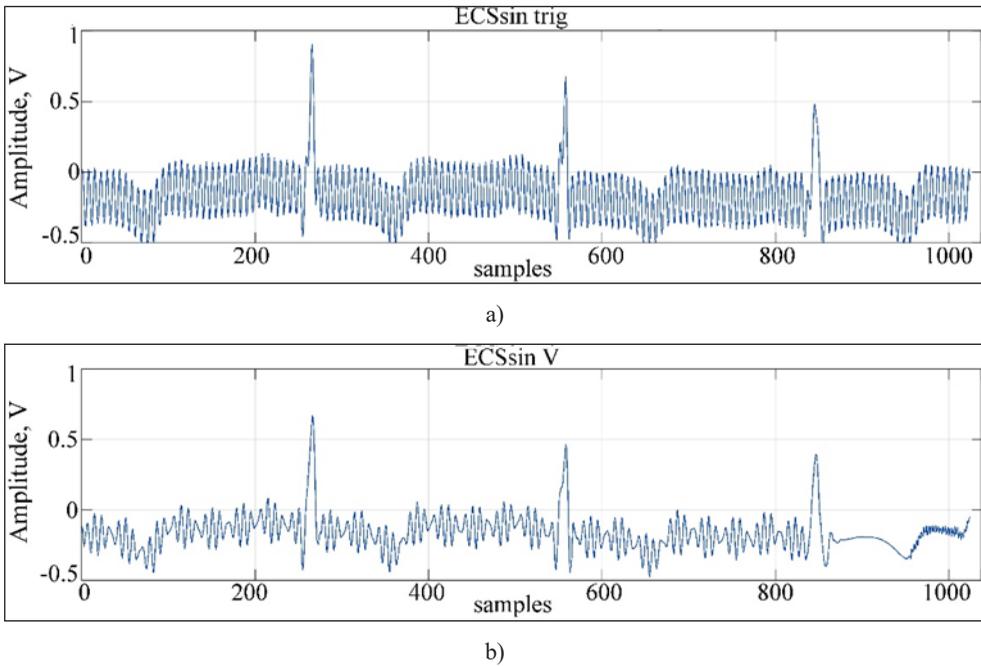


Figure 8. ECG signal with 50 Hz noise: a – Original; b – Restored

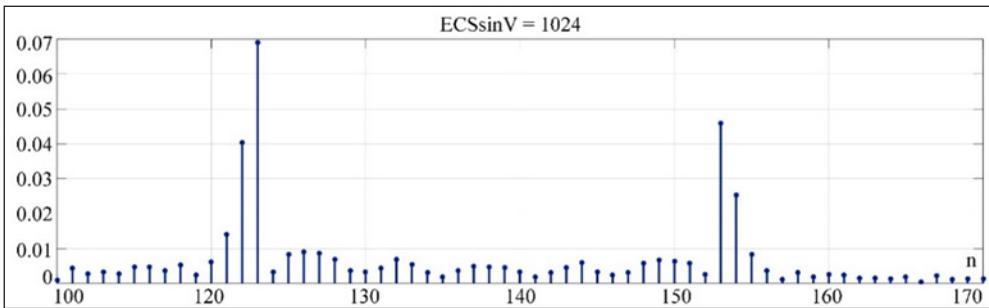


Figure 9. Magnitude spectrum of the restored ECG signal

### Results of Filter Development and ECG Signal Processing Research

To suppress interference with two adjacent harmonics, the windowing method with the Kaiser window function was selected. The design of the notch filter was based on determining the coefficients using the kaiserord method at a sampling frequency of 357 Hz. The boundary frequencies were set to 24.4, 34.4, 55.9, and 65.9 Hz. The vector of the ideal amplitude-frequency response was specified as [1 0 1], with allowable deviations of [0.05 0.01 0.05]. Based on these parameters, an FIR filter with a Kaiser window was calculated, ensuring suppression of harmonic components within the specified range. The obtained filter coefficients were imported into the Simulink model for subsequent simulation Figure 10.

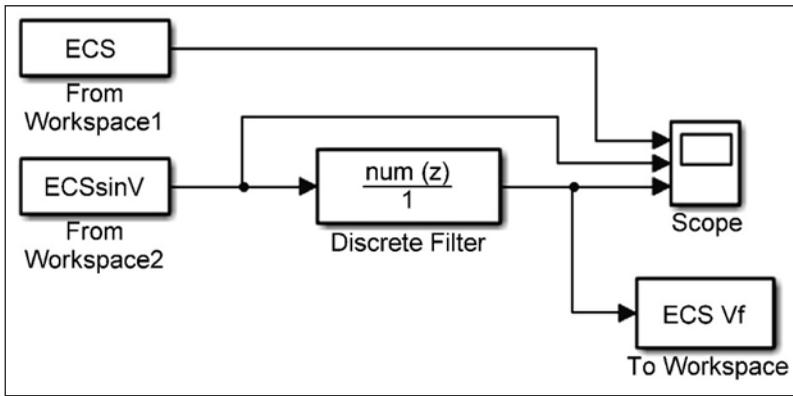
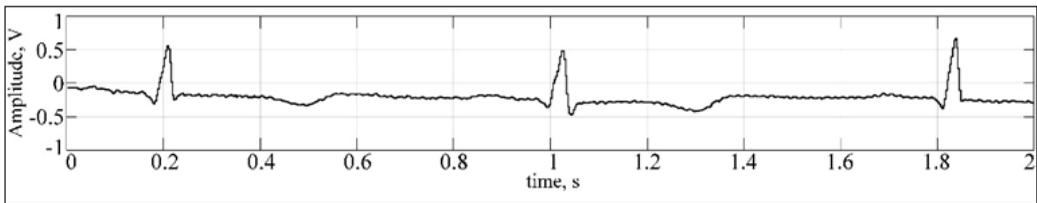
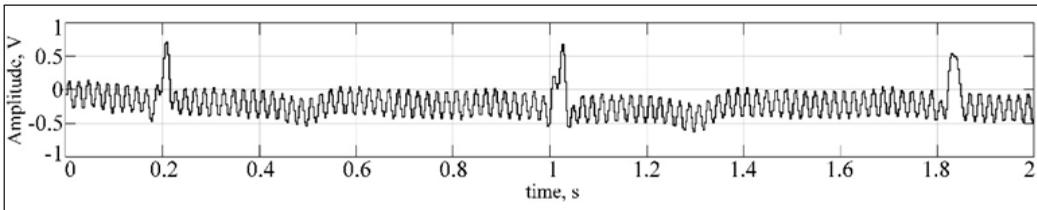


Figure 10. Simulink model for band stop filtering of ECG

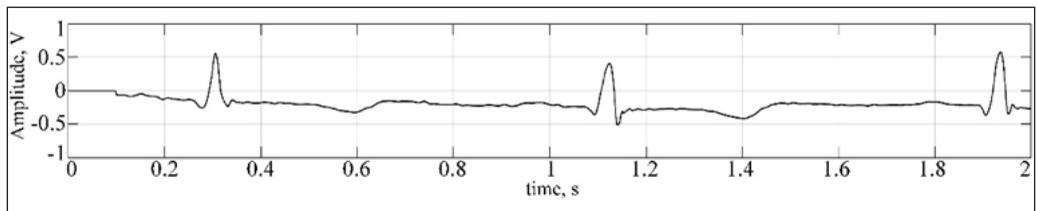
The results of the filtering process simulation on the Simulink model are shown in Figure 11.



a)



b)



c)

Figure 11. Results of band stop filtering of ECG: a – Original signal (Figure 4a); b – Reconstructed signal (Figure 8b); c – Signal after filtering

Thus, after wavelet transformation, Wi-Fi transmission, and band-stop filtering, we obtain a signal free from high-frequency noise and 50 Hz interference.

The next task for the system's receiving block is to remove the low-frequency component of the ECG, i.e., the baseline drift. To address this task, it is also advisable to use the windowed filtering method with the kaiserrord function. The coefficients for the high-frequency filter are determined for boundary frequencies outside the range of the useful signal frequencies. The contents of the b.mat file, saved to the Workspace, are inserted into the numerator of the discrete filter in the Simulink model shown in Figure 12.

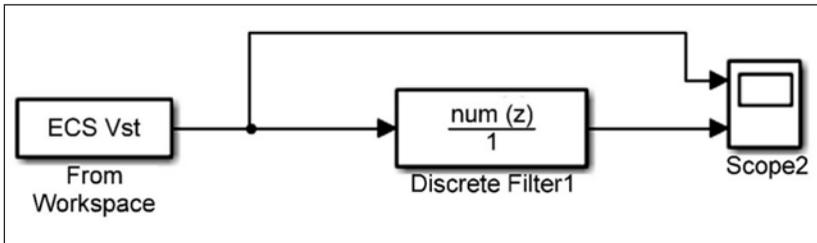


Figure 12. Simulink model for ECG high-frequency filtering

The input signal is the ECG signal obtained from the output of the band stop filter Figure 11c. The simulation results are presented in Figure 13.

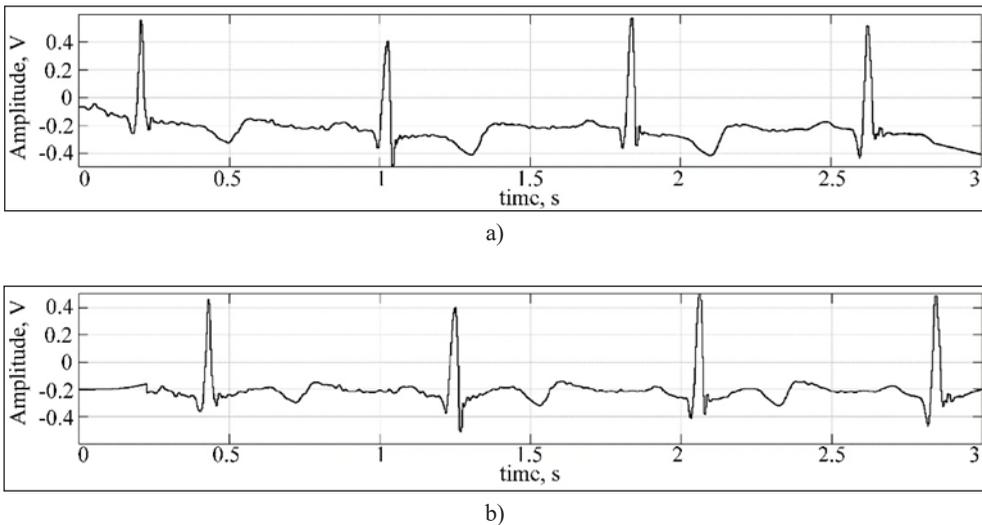


Figure 13. Results of high-frequency filtering of ECG: a – Original signal; b – Signal after filtering

Visual analysis of the high-frequency filtering results Figure 13 shows that the baseline drift in the output signal is virtually absent.

A particular noise class includes those caused by muscle activity, motion interference related to skin deformation and changes in skin potential, as well as noise related to electrode polarisation, breathing effects, changes in skin-electrode potentials, and inter-electrode impedance (Seena et al., 2014). This results in noise with a random, a priori unknown frequency spectrum overlapping with the spectrum of the useful signal, making its removal without distorting the useful signal a significant challenge.

This issue is especially acute when identifying the P wave, which has a low amplitude, and its identification in the presence of the mentioned noises can be very challenging. Additionally, detecting P waves during real-time signal analysis is complicated by the low signal-to-noise ratio for P waves and their low amplitudes compared to the QRS complex waves. This problem could be addressed using a classical single-layer linear neural network with a delay line, including two delay taps. The following equation describes the output of such a filter:

$$a(k) = \sum_{i=1}^3 w_{1i} a(k - i + 1) + b \quad [3]$$

A distinctive feature of the presented filter is its tuning, which aims to exclude amplitude-limited oscillations or outliers in the frequency spectrum of the useful signal at the filter's output. Previous filters have already cleaned the remaining frequency range of noise. The shape of the P wave remains unchanged. This processing is applied to the 0.3-second interval to the left of the QRS complex.

For the implementation of the filter, a single-layer linear neural network with a two-step delay was used. The input data covered the range of 0-0.3 s relative to the QRS complex. The network architecture included one neuron with delays [0 1 2], a learning rate of 0.01, and 10,000 training epochs. Input and target vectors were formed to ensure the suppression of low-amplitude oscillations while preserving the shape of the P wave. The dependency of the training quality on the number of cycles is shown in the graph in Figure 14.

Then, using the `genism(net)` command, a Simulink model of the obtained neural network filter is created, which is used in constructing the model of the noise filtering system in the frequency range of the useful signal Figure 15.

Here, the test signal generator Figure 16 is a model of the P wave created using an input two-frequency sinusoidal signal as a mixture of the useful signal and noise, with the time range limited to one half-wave Figure 17a. The graphical interface serves as a coordinating buffer between the filter and the oscilloscope.

Figure 17a shows the graph of the input signal or the P wave model; Figure 17b shows the graph of the signal at the filter output. As seen from the figure, the noise is absent from

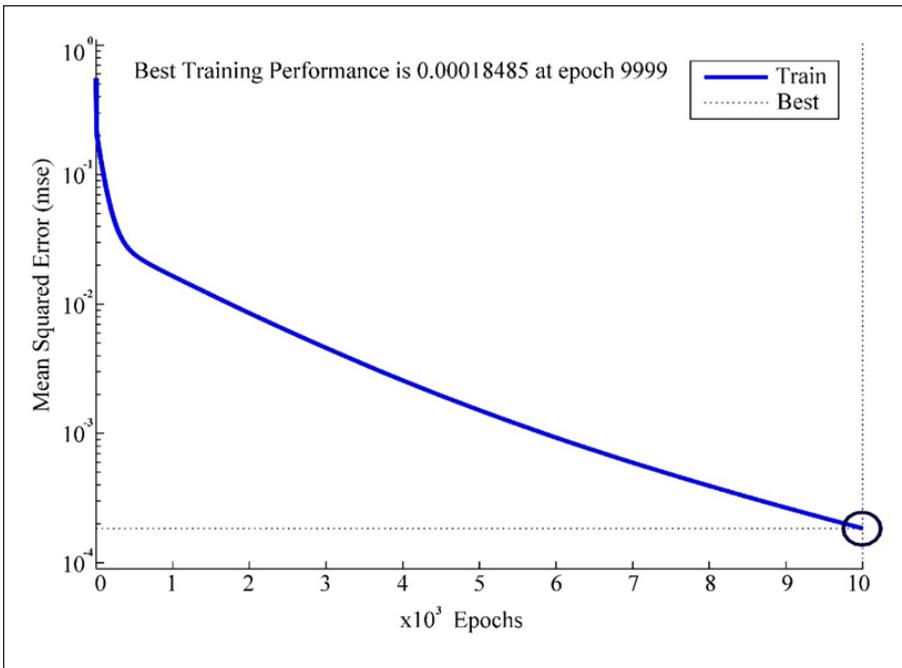


Figure 14. Dependence of the root mean square error on the number of training cycles

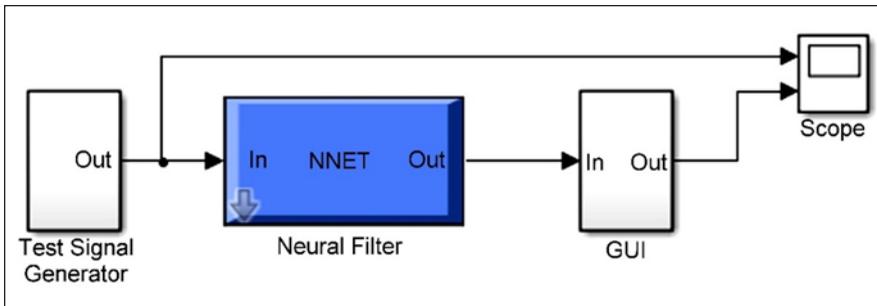


Figure 15. Simulink model of the neural network filter

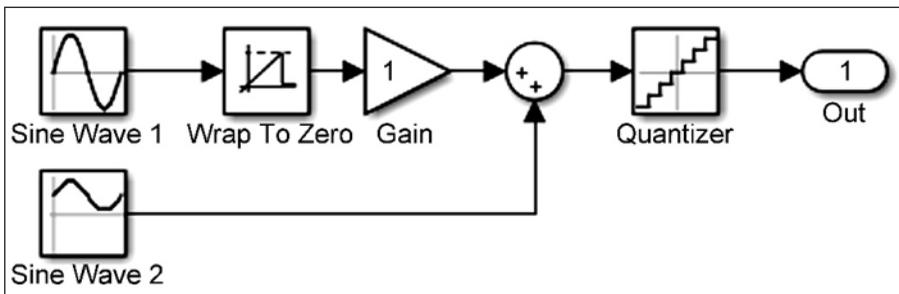
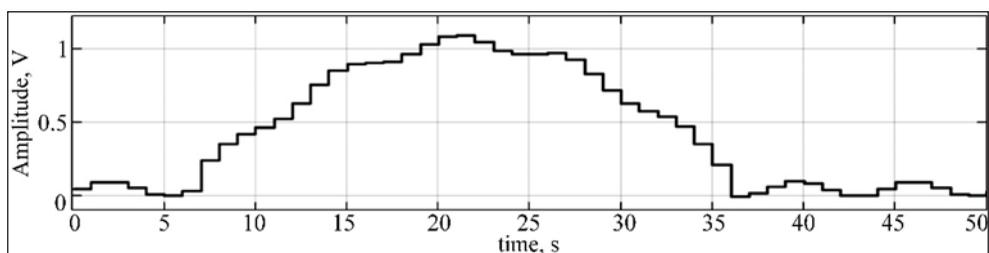
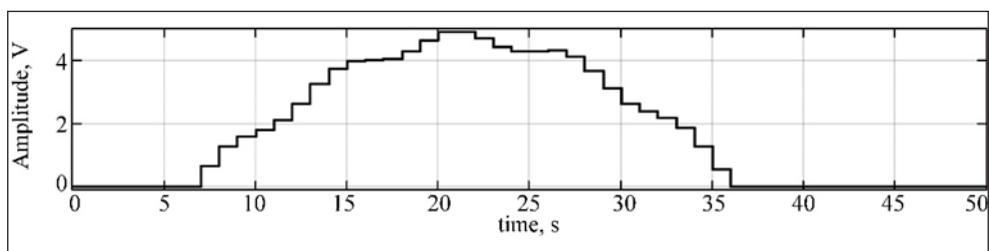


Figure 16. Simulink model of the test signal generator



a)



b)

Figure 17. Simulation results: a – P wave with noise; b – P wave after filtering

the output signal after filtering, and the amplitude of the useful signal (P wave model) increased fourfold.

## DISCUSSION OF THE RESULTS

The proposed structure of the wireless Holter monitoring system, based on modern component technology, allows the transmitting block of the system to perform discrete wavelet decomposition of the ECG. The developed ECG preprocessing algorithm for the Holter monitoring system provides eight-fold compression of the transmitted ECG data, high-frequency and low-frequency filtering of the ECG signal, as well as selective filtering to eliminate the 50 Hz noise. The proposed wavelet-based approach achieves an effective ECG signal compression ratio of approximately 8:1, while preserving diagnostically significant information for reliable analysis. Compared to the results reported by Devindi et al. (2024) and Elgendi et al. (2017), this represents a sufficiently strong performance. A neural network filter was also proposed to reduce the time required to recognise all ECG elements and improve P wave identification accuracy. Visual analysis of the obtained oscillograms shows that noise is absent after the signal transmission and processing procedure, and the useful signal (using the P wave model as an example) is increased fourfold. This enhancement of the useful signal with increased amplitude allows for improved quality of P wave identification and interpretation and other ECG characteristics.

The semi-physical modelling approach, on the one hand, enabled the transmission and reception of arrays of vectors  $C$  and  $L$  using real Wi-Fi equipment. On the other hand, complex computations of the forward and inverse wavelet transformations, as well as ECG signal interpretation, were performed using computer models. Plans include the full implementation of these processes by hardware.

The presented virtual complex for configuring and implementing the developing system algorithm provides a wide range of software and hardware tools, including specialised MATLAB packages for configuring, debugging, and optimising the operation modes of the real Holter monitoring system.

The work represents the initial stage in creating a wireless, high-performance, and cost-effective hardware-software ECG Holter monitoring system. The proposed method also has certain limitations, including the fact that the evaluation was carried out only on model datasets, which may constrain the generalisability of the results to real clinical environments. The next stage will focus on developing an algorithm for recognising all morphological elements of the ECG using classical and alternative (Koshekov et al., 2020) identification methods.

## CONCLUSION

The results of virtual experiments on implementing the ECG preprocessing algorithm showed that the chosen sequence and scope of filtering procedures can be considered optimal for ensuring the required quality of Holter monitoring.

The obtained time diagrams of real ECGs demonstrate that using wavelet transformation techniques for ECG signals allows for creating an effective Holter monitoring system that provides high-quality morphological analysis in rhythm and conduction disturbance cases. The results of semi-physical modelling demonstrated the feasibility of integrating microcontrollers with ARM Cortex™-M3 cores and next-generation Wi-Fi transceivers. Using original circuit and software solutions to increase noise immunity and minimise Wi-Fi device power consumption has enabled the development of a cost-effective and efficient ECG Holter monitoring system. Plans include expanding wavelet analysis for extracting morphological elements of the ECG and enhancing the assessment of individual ECG wave parameters. Additionally, there are plans to incorporate neural network technology for classifying recorded ECGs and utilising ECG data for safe user authentication to various information systems, as well as for assessing emotional states and hidden intentions (Sulavko et al., 2020).

When building stationary ECG monitoring systems, it is advisable to apply band-stop filtering at the initial stage, as processing is done directly on a personal computer, and there are no limitations on software resources. Furthermore, in Holter monitoring, the trade-off between signal compression and quality of low-frequency filtering is determined based on

the requirements for the duration of autonomous operation or power consumption of the Wi-Fi signal transmission device. Conversely, in standard ECG examinations, the main requirement for applying discrete wavelet transformation is the quality of low-frequency filtering. A particular issue arose when constructing the band stop filter. Using a filter tuned to remove a 50 Hz harmonic did not yield results. Only spectral analysis of the ECG revealed that after performing the direct and inverse discrete wavelet transforms, two harmonics appeared in the signal instead of one. Taking these into account in the filter design provided the desired result.

## ACKNOWLEDGEMENT

This research is funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP19677288).

## ABBREVIATION

DWT	:	Discrete wavelet transform
ECG	:	Electrocardiogram
ECS	:	Electro cardio signal
FIR	:	Finite impulse response
CWT	:	Continuous wavelet transform

## REFERENCES

- Asif, M. S., Faisal, M. S., Dar, M. N., Hamdi, M., Elmannai, H., Rizwan, A., & Abbas, M. (2023). Hybrid deep learning and discrete wavelet transform-based ECG biometric recognition for arrhythmic patients and healthy controls. *Sensors*, 23(10), Article 4635. <https://doi.org/10.3390/s23104635>
- Benmessaoud, A. S., Medjani, F., Bousseloub, Y., Bouaita, K., Benrahem, D., & Kezai, T. (2023). High-quality ECG dataset based on MIT-BIH recordings for improved heartbeat classification. In *2023 IEEE International Conference on Omni-layer Intelligent Systems (COINS)* (pp. 1-4). IEEE. <https://doi.org/10.1109/COINS57856.2023.10189299>
- Cai, Z., Li, J., Zhang, X., Shen, Q., Murray, A., & Liu, C. (2019). How accurate are ECG parameters from wearable single-lead ECG system for 24-hour monitoring. In *2019 Computing in Cardiology (CinC)* (pp. 1-4). IEEE. <https://doi.org/10.22489/CinC.2019.187>
- Chuiko, G., Dvornik, O., Darnapuk, Y., & Baganov, Y. (2021). Devising a new filtration method and proof of self-similarity of electromyograms. *Eastern-European Journal of Enterprise Technologies*, 4(9-112), 15-22. <https://doi.org/10.15587/1729-4061.2021.239165>
- Devindi, H. K. I., Ratnayake, P. R., Dissanayake, D. W. K., Munasinghe, D. G. S., & Samarasinghe, T. (2024). A real-time, low-complexity ECG compression scheme based on PWM and low-resolution quantisation. *Scientific Reports*, 14, Article 15414. <https://doi.org/10.1038/s41598-024-68022-5>

- Elgendi, M., Eskofier, B., Dokos, S., & Abbott, D. (2017). A review of QRS detection algorithms based on digital signal processing techniques. *Scientific Reports*, 7, Article 43663. <https://doi.org/10.1038/s41598-017-00540-x>
- Gerasimova, Y., Ivel, V., Moldakhmetov, S., & Petrov, P. (2024). Hardware-software implementation of a local Wi-Fi network for the transmission of biomedical signals. *Eastern-European Journal of Enterprise Technologies*, 4(9-130), 34-43. <https://doi.org/10.15587/1729-4061.2024.309387>
- Gerasimova, Y., Sidi, F., Ivel, V., Avdeyev, V., Abdullah, L. N., & Moldakhmetov, S. (2025). Automated real-time electrocardiogram diagnosis based on the modified Pan-Tompkins algorithm for long-term monitoring systems. *Eastern-European Journal of Enterprise Technologies*, 4(5-136), 15-27. <https://doi.org/10.15587/1729-4061.2025.336172>
- Harang, R., Bonnet, G., & Petzold, L. R. (2012). WAVOS: A MATLAB toolkit for wavelet analysis and visualisation of oscillatory systems. *BMC Research Notes*, 5, Article 163. <https://doi.org/10.1186/1756-0500-5-163>
- Ivel, V. P., Gerasimova, Y. V., Moldakhmetov, S. S., Petrov, P. A., Gerasimov, I. A., & Zainchkovskaya, K. V. (2019). Wireless three-channel Holter monitoring system. *IOP Conference Series: Materials Science and Engineering*, 537, Article 032090. <https://doi.org/10.1088/1757-899X/537/3/032090>
- Jain, A., Verma, A., Verma, A. K., & Bajaj, V. (2024). Tunable Q-factor wavelet transform-based identification of diabetic patients using ECG signals. *Computer Methods in Biomechanics and Biomedical Engineering*, 1-10. <https://doi.org/10.1080/10255842.2024.2342512>
- Khong, W. L., Mariappan, M., & Chong, C. S. (2021). Contact and non-contact heart beat rate measurement techniques: Challenges and issues. *Pertanika Journal of Science and Technology*, 29(3), 1707-1732. <https://doi.org/10.47836/pjst.29.3.03>
- Koshekov, K., Kobenko, V., Koshekov, A., & Moldakhmetov, S. (2020). Hand-written character structure recognition technology on the basis of identification measurements. *ARPJ Journal of Engineering and Applied Sciences*, 15(21), 2555-2562. [https://www.arpnjournals.org/jeas/research\\_papers/rp\\_2020/jeas\\_1120\\_8390.pdf](https://www.arpnjournals.org/jeas/research_papers/rp_2020/jeas_1120_8390.pdf)
- Kumar, A., Tomar, H., Mehla, V. K., Komaragiri, R., & Kumar, M. (2021). Stationary wavelet transform-based ECG signal denoising method. *ISA Transactions*, 114, 251-262. <https://doi.org/10.1016/j.isatra.2020.12.029>
- Li, N., Lin, M., & Li, F. (2019). Wearable bioelectrical impedance monitor based on ADuCM350. In *2019 12th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)* (pp. 1-3). IEEE. <https://doi.org/10.1109/CISP-BMEI48845.2019.8965939>
- Lin, M., Hong, Y., Hong, S., & Zhang, S. (2024). Discrete wavelet transform-based ECG classification using gcForest: A deep ensemble method. *Technology and Health Care*, 32(S1), 95-105. <https://doi.org/10.3233/THC-248008>
- Maleki, M., & Haeri, F. (2024). Identification of cardiovascular diseases through ECG classification using wavelet transformation (arXiv:2404.09393) [Preprint]. *arXiv*. <https://doi.org/10.48550/arXiv.2404.09393>
- Malik, S. A., Parah, S. A., Aljuaid, H., & Malik, B. A. (2023). An iterative filtering-based ECG denoising using lifting wavelet transform technique. *Electronics*, 12(2), Article 387. <https://doi.org/10.3390/electronics12020387>

- Mohonta, S. C., Ghosh, S., & Saha, G. (2022). ECG arrhythmia classification using 2D-CNN and continuous wavelet transform. *Sensing and Bio-Sensing Research*, 36, Article 100481. <https://doi.org/10.48550/arXiv.1804.06812>
- Sahoo, J. P., Prakash, A. J., Pławiak, P., & Samantray, S. (2022). Real-time hand gesture recognition using fine-tuned convolutional neural network. *Sensors*, 22, Article 706. <https://doi.org/10.3390/s22030706>
- Seena, V., & Yomas, J. (2014). A review on feature extraction and denoising of ECG signal using wavelet transform. In *2014 2nd International Conference on Devices, Circuits and Systems (ICDCS)* (pp. 1-6). IEEE. <https://doi.org/10.1109/ICDCSyst.2014.6926190>
- Setiawidayat, S. (2023). Discrete electrocardiogram T amplitude detection based on cycle duration. *Eastern-European Journal of Enterprise Technologies*, 3(9-123), 94-105. <https://doi.org/10.15587/1729-4061.2023.282759>
- Shaikh, M. U., Adnan, W. A., & Ahmad, S. A. (2020). Secured electrocardiograph (ECG) signal using partially homomorphic encryption technique–RSA algorithm. *Pertanika Journal of Science and Technology*, 28(S2), 231-242. <https://doi.org/10.47836/pjst.28.s2.18>
- Singh, P., Shahnawazuddin, S., & Pradhan, G. (2017). Significance of modified empirical mode decomposition for ECG denoising. In *2017 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 2956-2959). IEEE. <https://doi.org/10.1109/EMBC.2017.8037477>
- Slyusar, V., Protsenko, M., Chernukha, A., Gornostal, S., Rudakov, S., Shevchenko, S., Chernikov, O., Kolpachenko, N., Timofeyev, V., & Artiukh, R. (2021). Construction of an advanced method for recognising monitored objects by a convolutional neural network using a discrete wavelet transform. *Eastern-European Journal of Enterprise Technologies*, 4(9-112), 65-77. <https://doi.org/10.15587/1729-4061.2021.238601>
- Sulavko, A. E., Lozhnikov, P. S., Choban, A. G., Stadnikov, D. G., Nigrey, A. A., & Inivatov, D. P. (2020). Evaluation of EEG identification potential using a statistical approach and convolutional neural networks. *Informatsionno-Upravliaiushchie Sistemy*, 6, 37-49. <https://doi.org/10.31799/1684-8853-2020-6-37-49>
- Wang, T., Lu, C., Sun, Y., Yang, M., Liu, C., & Ou, C. (2021). Automatic ECG classification using continuous wavelet transform and convolutional neural network. *Entropy*, 23(1), Article 119. <https://doi.org/10.3390/e23010119>