Journal of Computer Science

Original Research Paper

Methodological Approach to Developing a Model of Interference-Free Processing of Multichannel Records of the Electrical Cardiological Impulse to Determine Episodes of Cardiac Muscle Ischemia

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Article history
Received: 28-11-2024
Revised: 26-12-2024
Accepted: 07-01-2025

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Abstract: This study considered a set of topical issues aimed at improving the methodology of the early recognition of episodes of myocardial ischemia. It aims to solve a set of problems in the substantiation and development of a methodological approach for building a model of interference-free processing of multichannel electrocardio signal recordings. Based on theoretical and experimental studies, this will create new methods of increased interference resistance to recognize the phases of cardiac muscle ischemia. This study focused on the development of multiple simulations of changes in electrical cardiac impulse in several branches during the progress of cardiac muscle ischemia, including the influence of muscle noise. This study analyzed existing methodological approaches for the early detection of Ischemic Heart Disease (IHD) and electrocardio signal processing, analysis and classification, which are the most promising methods for detecting and classifying myocardial ischemia. The relevance of a technique for detecting IHD phases using multiple simulations of electrical cardiac impulses and their change in ST segments in different branches, considering the combined effect of the noise component, was substantiated. The importance of its implementation within the framework of an operational automated system for detecting life-threatening episodes of myocardial ischemia has been emphasized. The proposed solution makes it possible to rely on the automatic and interference-resistant detection of IHD phases in interference-distorted segments of electrical cardiac impulses. The results demonstrated the practical coincidence of the experimentally and theoretically obtained data on the probability of decision-making for one of the IHD phases. A study undertaken in conjunction with the I.M. Sechenov First Moscow State Medical University, as part of a world-class research centre, revealed that the discrepancy between practical and theoretical data was less than 5%.

Keywords: Electrical Cardiac Impulse, Electro Cardio Graphy (ECG), Interference-Free, Methodological Approach, Myocardial Ischemia, Processing

Introduction

Ischemic Heart Disease (IHD) is a well-known and dangerous disease of the Cardio Vascular System (CVS). This disease is inherent in the absolute or relative disturbance of blood flow in the heart muscle. The progression of the IHD phase usually depends on increased emotional or physical strain, which in most cases is aggravated by painful sensations. Nevertheless, IHD can also occur in fully painless forms (as a rule, more than one-third of patients do not realize the existence of IHD) (Franco *et al*., 2011).

Currently, the most common method for diagnosing this disease is electrical cardiography, which is performed against the background of monitoring Electrical Cardiac Impulses (ECI) or stress tests. Simultaneously, during registration, the format of electrical cardiac impulses is affected by interfering components and distortions that significantly complicate the decoding of the received electrical cardiac impulses. Particular difficulties relate to the processing of screen recordings taken during 24 h, which contain noisy segments of electrical cardiac impulses recorded under load when the registration of IHD phases seems most likely.

The results of the experiments show that if the data describing the structure and crucial characteristics of electrical cardiac impulses are recorded on several branches, it is possible to significantly improve the accuracy of the IHD phase diagnosis. Currently, many channel complexes are used to monitor the electrical cardiac impulses. As a result, specialized professionals can quickly recognize IHD in patients, preventing the dangerous progression of conditions that threaten their physical existence. Simultaneously, creating methods and tools to evaluate the multichannel recordings of electrical cardiac impulses is a complicated problem (Polezhaev *et al*., 2023).

Currently, computerized methods capable of efficiently evaluating multichannel recordings of electrical cardiac impulses against the background of complex interfering components are necessary. The development of methods for the automated assessment of electrical cardiograms, especially multichannel ones, is limited by difficulties in simultaneously simulating changes in electrical cardiologic impulses along several branches and the cumulative effect of their noise components.

To solve these problems, it is necessary to develop special techniques and programmable systems to process multichannel electrical cardiac impulses.

This study aimed to solve problems related to the substantiation and development of a methodological approach for building a model of an interference-free circuit for processing multiple-channel registrations of electrical cardiac impulses. This will be the basis for special techniques with increased resistance to interfering components during automated diagnosis of IHD phases. Despite the multitasking nature of this process, this study focused on developing a multistage simulation of changes in electrical cardiac impulses recorded on several branches during the progression of the IHD phases, including the influence of the interfering component.

Literature Review

Several research methods can be used to diagnose cardiac muscle ischemia Fig. (1).

The diagnosis of IHD based on the predominant research techniques shown in Fig. (1) usually relies on assumptions. For this reason, it is more common to use device-based investigations, in other words, to perform diagnostic procedures using specialized medical systems. They help detect ischemia of the cardiac muscle in the early stages with more significant reliability, identify the features of the course of this pathology, and perform forecasts of further development. For these purposes, a broad range of techniques (electrical cardiography, gamma scanning of the cardiac muscle, stress testing, etc.) are used (as reflected in Table 1), the critical of which is Electro Cardio Graphy (ECG). This technique relies on recording electrical cardiac impulses on several branches, further revealing the differences in the biological potentials formed during contraction. Evaluation of the results of this technique opens up the possibility of reliable recognition of the development of IHD phases and identification of the affected areas of the cardiac muscle, which is necessary for cardiologists (Ansari *et al*., 2017).

The assessment of the presented methods for diagnosing cardiac muscle ischemia allowed us to draw several conclusions:

- Techniques are applicable exclusively in medical institutions and their implementation requires the participation of trained specialists. Therefore, the use of these techniques in the initial stages of cardiac muscle ischemia diagnosis is challenging
- CT-based methods have some inherent limitations owing to the need for exposure to radiation loads and the need to administer contrast agents to patients

Recording changes in electrical cardiac impulses on electrocardiograms is reliable and sufficient for recognizing IHD because the technique has low sensitivity. However, detecting a more serious change requires further examination of patients because the technique is sufficiently specific.

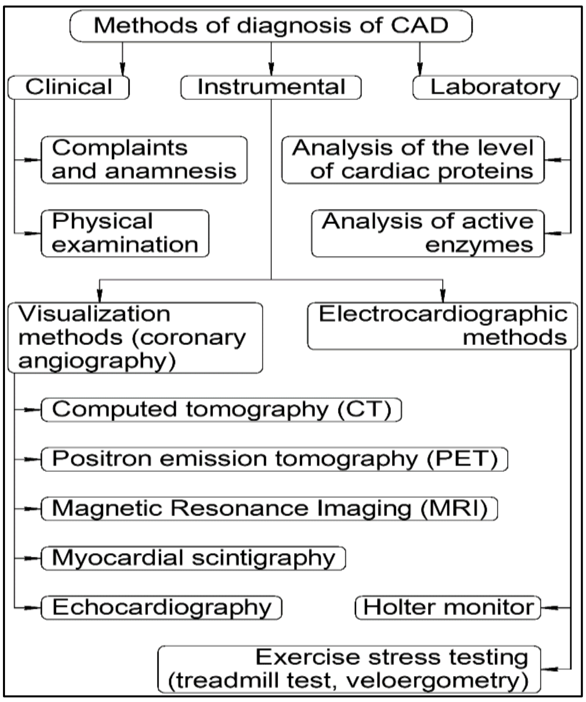

Fig. 1: Classification of IHD diagnostic techniques

Table 1: Assessment of techniques for hardware diagnosis of cardiac muscle ischemia

Technique	Advantages	Disadvantages
Performing a stress electrocardiogram	Widespread, uncomplicated procedure, a reasonable cost	Need for physical activity
Scintigraphic study of perfusion	Standard and common research procedure	Presence of radiation exposure
Computer Tomography (CT)	Accelerated acquisition of medical data, visualization of affected areas	Limited use of the technique
Magnetic Resonance Tomography (MRT)	Clear visualization of cardiac muscle structure and features. Possible visualization of the consequences of Acute Myocardial Infarction (AMI)	Use of expensive medical systems
Computed Tomography angiography (CT angiography)	Accelerated acquisition of medical data, ability to visualize adjacent tissues	Presence of radiation exposure, use of contrast agents
Magnetic Resonance Angiography (MRA)	No radiation exposure	Comparatively low visualization clarity
Electron-Beam Tomography (EBT)	Possibility to visualize the smallest areas	Use of contrast agents, the technique is characterized by high and technical costs

Materials and Methods

To analyze the diverse methodological approaches used to assess the most common existing processing techniques and study electrical cardiac impulses for recognizing cardiac muscle ischemia, we summarized their features and properties in Table (2).

The data summarized in Table (2) reflect the development and practical use of a wide range of diverse methodological approaches for the assessment and classification of electrical cardiac impulses for IHD recognition.

Most available techniques for the automatic detection of cardiac muscle ischemia rely on wave transformations, decision rules, neural networks and base gradients. In the majority of the transform methods that have been presented, such as the wavelet transform and Fourier transform, the presence of noise signals on the system input results in interference from the power grid, which is a problematic element in the analysis. This is due to the fact that the frequency of the noise signals is within the same range as the frequency of the ECG signals. Consequently, to enhance the noise immunity of the algorithm for automated detection of episodes of myocardial ischemia, it is imperative to develop a method for signal transformation that is resistant to interference.

The specificity of cardiac muscle ischemia diagnostics is necessary to register a patient's electrical cardiac impulses in a calm state and under load. Monitoring for 24 h has several advantages over recording electrical cardiac impulses in a calm state. These advantages open up the possibility of recognizing life-threatening phases of cardiac ischemia, whereby the duration of heart rhythms, frequency and other parameters can be recorded for 24 h. Therefore, it is necessary to develop automatic medical complexes capable of recognizing critical IHD phases with high accuracy to reduce screen image decoding time and workload of cardiologists (Alexandrov *et al*., 2023).

Accurate identification of IHD phases requires branch groups such as those that capture the most informative electrical cardiac impulses for more reliable IHD identification. However, specialists must generalize the data obtained during the assessment of the multichannel recordings of electrical cardiac impulses.

The techniques available for assessing multiple-channel recordings of electrical cardiac impulses Table (3) can be categorized as follows:

- The ability to simultaneously assess electrical cardiac impulses from any branch to summarize this information
- The application to identify medical information from a single branch

The main research results in Table (3) confirm that the considered variants of data summarization were obtained without creating a multistage simulation of electrical cardiac impulses, which considers the presence of mutual connections between the impulses and interfering components of the electrical cardiac impulse recorded for several branches.

Creation of a Simulation of Interference-Resistant Assessment of Multichannel Registrations of Electrical Cardiac Impulses Necessary for Recognizing Phases of Cardiac Muscle Ischemia

The problem caused by the creation of the myographic interference simulation is that the considered interfering component present in i^{th} branches of the electrical cardiac impulse is broadband noise described by the ratio $\left(\sigma_j^{\langle i\rangle}\right)^2$ representing a constant value in the given j^{th} cardiac period. The physical basis of this simulation is as follows: The interfering component forms owing to muscle fiber motion characterized by different frequency oscillations at various time intervals and this, considering the central theory of limits, forms the base mathematical simulation. However, this simulation can describe noise only in certain (i^{th}) branches, but the problem of creating a simulation representing myographic interference recorded in all branches at once is still relevant (Blanco-Velasco *et al*., 2008).

Table 2: List of the most common assessment techniques for electrical cardiac impulses concerning the detection and classification of cardiac muscle ischemia

Approach to analyzing and classifying ECG signals	Features	Notes
Classification based on the linear discriminant assessment and the decision tree technique (Wang *et al*., 2015)	A list of frequency and temporal indicators of the QRS system, including their potential, QRS system rise and fall and highest QRS system power and frequencies here represent initial information	Standardized information arrays, e.g., PhysioNet and others, were used
A technique based on the application of main components (Castells *et al*., 2007)	It relies on the simultaneous use of main component techniques and neural networks	The obtained information can be more accurately classified to reduce their dimensionality, which provides a more reliable diagnosis of cardiac muscle ischemia
A technique based on the application of the electrocardiogram QRS system dependence with high detail (Farashi, 2016)	Electrocardiograms are processed by wave transformations of averaged cardiac impulses of 240-250-point dimension and then key features are separated owing to the use of linear assessment and the main component techniques	Using linear assessments and the main component technique allows for a more accurate separation of helpful characteristics
Classification of electrical cardiac impulses using neural networks (Jayachandran *et al*., 2010)	Several options are used to classify the electrocardiogram impulses through neural network techniques and base gradients	The technique can detect various diseases and perform biometric studies.
A technique based on the application of filtering neural networks (Pławiak, 2018)	The convolutional neural network (CNN) deep machine learning process is performed	It makes it possible to detail various types of electrocardiograms in 94-95.2% of cases
A technique based on special impulses of stress electrocardiograms, where it is possible to separate the main parts of cardiograms, for example, QRS systems (Anbalagan *et al*., 2023)	ST segment estimation is performed on frequencies and time	Different ST segment amplitudes can be recorded in various courses of cardiac muscle ischemia
A technique based on neural network simulation capable of reducing the size of information arrays formed by multichannel registration of electrocardiograms (Taddei *et al*., 1992)	The helpful simulation features built on training are considered, while the neural network performs the impulse classification	The technique makes it possible to separate helpful characteristics for their further classification
A technique based on the assessment of R-elevations and R-R segments of the electrocardiogram (Park *et al*., 2012)	The main sorter is the k-nearest neighbor methodology, solving trees and base gradients	The reliability of classification is 89-92%
A technique based on the detection of pathologies displayed by ST segments (Murugan and Radhakrishnan, 2010)	A structured feature gradient is used to analyze the ST segment data, classifying it using the base gradient technique	The methodology demonstrates reliability at the level of 93.29%
A technique for diagnosing cardiac muscle ischemia using electrocardiograms and QRS dependencies (Kumar and Singh, 2016)	The first step involves segmenting the electrocardiogram impulses into some cardiac periods and then using wave transformation. It is not uncommon to apply sorters such as base gradients	The classification is performed using the minimum base gradients technique and the accuracy is 99.29%
A technique for detecting ischemic episodes in long electrocardiographic recordings in automated IHD diagnosis (Xie *et al*., 2020)	The technique is based on neural networks trained by Bayesian smoothing and main component estimation	The accuracy of the technique is about 89-90%
Automatic classification of cardiac muscle ischemia using neural networks (Elgendi *et al*., 2017)	The neural network applied is a multilevel artificial neuron. The gradient of characteristics resulting from the processing is minimized by the technique of main components	The accuracy of the technique is about 93-94%
Application of mathematical simulations of cardiac muscle ischemia diagnostics (Hussein *et al*., 2019)	The simulation of cardiac muscle ischemia diagnostics is based on the application of the classification evaluation technique	The technique is based on splitting the routes of moving row tables, obtaining helpful characteristics sent to the input channels of neural network sorters
An approach based on morphologic and energetic features of ECG (Han and Shi, 2019)	The main characteristics are QRS systems, P, T spectra, ST segments, PR and QT intervals. Classification of information is performed using the technique of base gradients	The specificity of the obtained electrocardiogram is considered; automatic categorization of cardiograms into the categories of “no ischemia” and “ischemia present” is performed
A technique based on computer-assisted detection of ST segment changes (Correa *et al*., 2013)	The base is a wave transformation, necessary to identify QRS systems in electrical cardiac impulses. Here, the neural network acts as a sorter	The accuracy of the technique is 89-90%

DOI: 10.3844/jcssp.2025.1003.1014

Table 3: Techniques capable of automatically evaluating the multichannel recordings of electrical cardiac impulses

The essence of the approach realized in the method	Features	Notes
Data from several branches of electrical cardiac impulses are summarized by selecting the maximum value of ST segment shift for three branches of electrical cardiac impulses (Ghaffari *et al*., 2011)	The weakness of this technique is that there is insufficient data on noise in the branches of the electrical cardiac impulses. This results in data distortion if there is much noise in one branch and during subsequent generalization of the information	The technique implements the principle of parallel processing of each of the two or three different branches
The technique is based on the noise assessment for each of the two branches of the electrical cardiac impulses (Chiarugi *et al*., 2007)	Initial recognition of QRS systems is performed on all branches, followed by noise analysis for each branch of the electrical cardiac impulses. The final decision on the QRS system location comes after carefully assessing the branch with the lowest noise	The technique implements the principle of considering the information of only one of two different branches having the lowest noise level
A technique demonstrating the accuracy of detection and identification of QRS systems of different registrations of electrical cardiac impulses (Chen and Chuang, 2017)	The assessment excludes those branches where the chain of fifteen counts of assessed electrical cardiac impulses would be the largest or the smallest	The technique makes it possible to avoid processing low-informative parameters of electrical cardiac impulses
QRS systems are detected in any branch (Laguna *et al*., 1994)	The locations of individual *i*-th QRS systems are recorded in all branches. In case the results of the location analysis belong to the established time interval, the recognition of *i*-th QRS system is finished	The only branch that best meets the predetermined requirement is used
Parallel channel-by-channel analysis with further integration (according to some or other principles) of electrical cardiac impulses from different multichannel branches into a single signal (Papageorgiou *et al*., 2022)	Before combining into a single signal, the initial detection of QRS complexes in each channel occurs independently	Several generalizing factors may be used, such as quadratic, selection of the maximum magnitude of ST segment shift across all branches and calculation of the combination of electrical cardiac impulses in several branches
A technique that provides multichannel estimations of the format of QRS systems using an ideal electrical cardiac impulse (Boostani and Sabeti, 2018)	Classification of QRS systems is separate for each branch by calculating Dj distances among the QRS systems under study and *j*-th perfect impulses	The average distance for each branch is calculated by the ratio $D_{jcp} = \sqrt{\sum_{n=1}^{N} p_n^2}\,(D_j^2)^2$ here, *N*-the number of branches, *n*-branch index, *j*-classification index, p_n-mass indicators corresponding to the expression $\frac{1}{N-1}$
A technique based on the application of base gradients obtained from normally situated branches X, Y and Z (Murat *et al*., 2020)	The technique relies on helpful characteristics describing the QRS contour: The maximum potential of the gradient forming the QRS contour and the value of Z, which defines the potential of the gradient forming the ST segment	$\Delta_{ST} = \sqrt{\Delta_{ST_X}^2 + \Delta_{ST_Y}^2 + \Delta_{ST_2}^2}$ In this case, $\Delta_{ST_X}^2 + \Delta_{ST_Y}^2 + \Delta_{ST_2}^2$ display ST segment shift values by several branches
Parallel channel-by-channel analysis of the system of features of different branches of electrical cardiac impulses with the subsequent study of the obtained dataset using the technique based on the decision tree (Gnanvo *et al*., 2016)	Each cardiac period involves calculating the values of eighteen helpful characteristics based on the key protrusions and intervals of the impulse chain for several branches of the electrical cardiac impulses. A table is created and assessed using decision trees and vector magnification techniques	No information on branch noise is considered

Therefore, primary attention should be paid to the informative electrical cardiac impulses of i^{th} branch, generally described by the dependence $S^{\langle i\rangle}(q)$ reflecting the changes in the actual electrical cardiac impulse, when it, with some assumptions, can be assessed without the interfering component. In other words, the electrical cardiac impulse in i^{th} branch is the sum of the base impulse potential $S^{\langle i\rangle}(q)$ and interference $n^{\langle i\rangle}(q)$:

$$y^{\langle i\rangle}(q) = S^{\langle i\rangle}(q) + n^{\langle i\rangle}(q) \tag{1}$$

Here, $q = 1,2,3..., N$ is the index of the studied impulse, N is the number of counts of the considered chains, i represents a particular branch of the electrical cardiac impulse.

To separate the interfering component from the chain of the electrical cardiac impulse $y^{\langle i\rangle}(q)$, several methods can be used to estimate the actual format of the electrical cardiac impulse $\hat{S}^{\langle i\rangle}(q)$ in i^{th} branch. However, the most interesting aspect is the assessment technique of the format of the electrical cardiac impulse by the approximation of polynomials corresponding to the 1st and 2nd levels of protrusions and intervals of the cardiac period.

The developed technique facilitates the isolation of 'true' ECG signals by extracting the myographic interference. This is achieved by dividing the unnoised cardiac cycle into segments, which are then approximated using second-order polynomials.

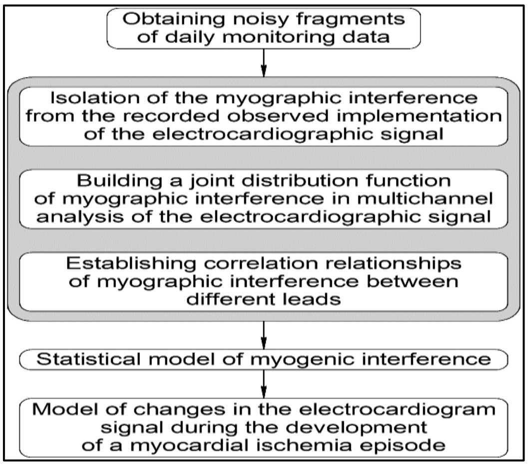

Fig. 2: External view of the proposed simulation of the recorded electrical cardiac impulse

In the simulation, the main difficulties with the interfering component separation were overcome by refusing to draw marking lines on the studied cardiac period and assessing the format of the electrical cardiac impulse $\hat{S}^{\langle i\rangle}(q)$ in i^{th} branches. This was done because of the approximation of relatively small segments of electrical cardiac impulses using polynomials, with a reduction to a common average of the approximated graphs (Fig. 2).

The essence of this proposal in formalized form is reduced to the following: The observed implementation of the electrocardiosignal splits $\hat{y}^{\langle i\rangle}(q)$ into small-count fragments $y_k^{\langle i\rangle}(q) = y^{\langle i\rangle}(k+q-1), k = 1,2,\dots,N-I+1$ of length I:

$$S_k^{\langle i\rangle}(q) = S^{\langle i\rangle}(k+q-1) = b_{2,k}^{\langle i\rangle}q^2 + b_{1,k}^{\langle i\rangle}q + b_{0,k}^{\langle i\rangle} \tag{2}$$

Here, q = 1,2,3…, I, I is the number of counts of the defined interval, k = 1,2,3…, N-I+1 is the index of the current interval and $b_{2,k}^{\langle i\rangle}q^2 + b_{1,k}^{\langle i\rangle}q + b_{0,k}^{\langle i\rangle}$ is a polynomial index.

At any k-th interval, a polynomial of the 2nd level $\hat{S}^{\langle i\rangle}(q)$ was used, which expresses the format of interference-free electrical cardiac impulses recorded in i^{th} branches:

$$\hat{S}^{\langle i\rangle}(q) = \hat{b}_{2,k}^{\langle i\rangle}q^2 + \hat{b}_{1,k}^{\langle i\rangle}q + \hat{b}_{0,k}^{\langle i\rangle}$$

Accordingly, k-th interval of the detectable chain of electrical cardiac impulses can be expressed as follows:

$$y_k^{\langle i\rangle}(q) = S_k^{\langle i\rangle}(q) + n_k^{\langle i\rangle}(q) = b_{2,k}^{\langle i\rangle}q^2 + b_{1,k}^{\langle i\rangle}q^1 + b_{0,k}^{\langle i\rangle}q + n^{\langle i\rangle}(k+q-1) \tag{3}$$

The averaged value $y_k^{\langle i\rangle}(q)$ will be identical to $m\{y_k^{\langle i\rangle}(q)\} = b_{2,k}^{\langle i\rangle}q^2 + b_{1,k}^{\langle i\rangle}q^1 + b_{0,k}^{\langle i\rangle}$ and also $D\{y_k^{\langle i\rangle}(q)\} = \left(\sigma_k^{\langle i\rangle}\right)^2$.

Simultaneously, the polynomial indices $b_{2,k}^{\langle i\rangle}q^2 + b_{1,k}^{\langle i\rangle}q + b_{0,k}^{\langle i\rangle}$are located in isolation concerning the current branch and are described by assessing the actual format of the electrical cardiac impulse recorded randomly in one of the branches.

In addition, we performed mass averaging of the intersecting approximate plots displaying sliding windows $\hat{S}(q) = \sum_{x=1}^{I}\beta_x\hat{S}_{q-x+1}(x)$, where $\beta_x$is the current mass exponent at which the variance of informative values will take the smallest value $D\{\hat{S}(q)\}$. This opens up the possibility of separating the interfering components:

$$\hat{n}^{\langle i\rangle}(q) = y^{\langle i\rangle}(q) - \hat{S}^{\langle i\rangle}(q) \tag{4}$$

In a noisy cardiac cycle, the greatest error in the estimation of the true shape of an Electro Cardio Gram (ECG) is observed in the region of the QRS complex. Consequently, the estimate of the average power of the extracted myographic noise is significantly different from its true value. However, if the QRS complex samples are excluded from consideration, the difference would be minimal. On average, the changes in the values are 35-40%

Experimentally, we obtained the average values of the interdependence indices of counts of multichannel muscle interference components extracted from the screen images, which represent $m(\hat{r})$ in this case (it is an interdependence indicator) if the number of counts is N ≈100. Among the counts of interfering components fixed in neighboring branches; a mutual relationship is determined by the type of muscle load:

$$\hat{r} = \frac{\sum_{q=1}^{N}\hat{n}^{\langle i\rangle}(q)\hat{n}^{\langle j\rangle}(q)}{\sqrt{\sum_{q=1}^{N}(\hat{n}^{\langle i\rangle}(q))^2\sum_{q=1}^{N}(\hat{n}^{\langle j\rangle}(q))^2}} \tag{5}$$

Figure (3) shows the noise counts by branch: (a) V4-V5 and (b) V5-V6.

The obtained information makes it possible to establish normalized moment values. Their correspondence to zero and the identity of their current orders confirm that the counts $n(q)$ chaotically forms normal gradients. In this case, the counts obtained at different time intervals do not depend on each other.

The range of results of the analytical and practical experiments obtained and described above allows us to conclude that the interfering component $n^{\langle i\rangle}(q)$ in i^{th} branch of the electrical cardiac impulse is broadband $\left(\sigma_k^{\langle i\rangle}\right)^2$ and its magnitude remains unchanged in k-th cardiac period.

The counts $n^{\langle i\rangle}(q)$ at several time intervals q_1 and on i-th branches of the electrical cardiac impulse are represented by non-interrelated values $m\{n^{\langle i\rangle}(q_1)n^{\langle i\rangle}(q_2)\} = 0, q_1 \neq q_2$. Simultaneously, among the counts of the noise component recorded on several branches of the electrical cardiac impulse, there is a specific interrelation and only on some time segments. Figure (4) shows the interfering component $n^{\langle 1\rangle}(q)$ and the noise component $n^{\langle 2\rangle}(q)$ recorded over several branches of the electrical cardiac impulse:

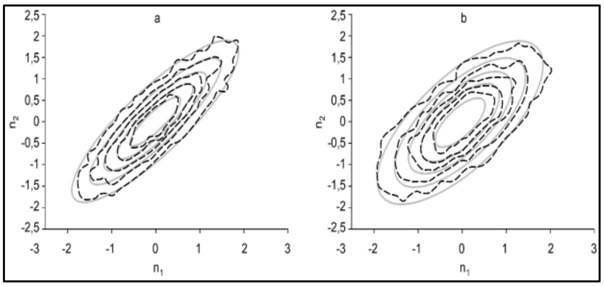

Fig. 3: External view of lines characterized by certain noise counts for branches (a) V4-V5; (b) V5-V6

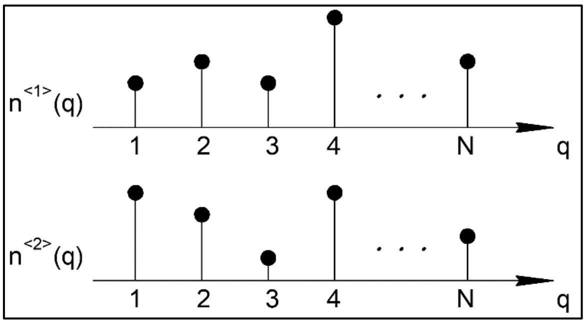

Fig. 4: External view of the noise component in two branches of the considered electrical cardiac impulse

$$n = \left(n^{\langle 1\rangle}(1), n^{\langle 2\rangle}(1), n^{\langle 1\rangle}(2), n^{\langle 2\rangle}(2), \dots, n^{\langle 1\rangle}(N), n^{\langle 2\rangle}(N)\right)^T \quad (6)$$

where, $n(q) = (n^{\langle 1\rangle}(q), n^{\langle 1\rangle}(q))^T, q = 1,2,\dots,N$ is the count's number.

It makes sense to use the correlation matrix Σ concerning multistage simulation chains of counts of normal gradients n within an assessed cardiac period (interval N of counts); that is, $N \times N$:

$$\Sigma = \begin{pmatrix} K & 0 & 0 & \dots & 0 \\ 0 & K & 0 & \dots & 0 \\ 0 & 0 & K & \dots & 0 \\ \dots & \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & 0 & K \end{pmatrix} \quad (7)$$

where, K is the correlation matrix of the gradient $n(q)$, corresponding to:

$$K = \begin{pmatrix} \sigma_1^2 & K_{12} \\ K_{21} & \sigma_2^2 \end{pmatrix} \quad (8)$$

$K_{12} = K_{21} = m\{n^{\langle 1\rangle}(q) n^{\langle 2\rangle}(q)\}$ is the correspondence of counts on two branches of the electrical cardiac impulse on a one-time interval $q, q = 1,2,\dots,N, D\{n^{\langle i\rangle}(q)\} = \sigma_i^2$. This shows the splitting of the noise component in i^{th} branch (i = 1, 2), representing a constant value within the investigated cardiac period. The opposite situation is Σ^{-1} when Σ can be described as:

$$\Sigma = \begin{pmatrix} K^{-1} & 0 & 0 & \dots & 0 \\ 0 & K^{-1} & 0 & \dots & 0 \\ 0 & 0 & K^{-1} & \dots & 0 \\ \dots & \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & 0 & K^{-1} \end{pmatrix} \quad (9)$$

where, Σ has a stable relationship with K ratio:

$$det(\Sigma) = (det(K))^N$$

When $K_{ij} = K_{ji}$:

$$det(K) = \sigma_1^2\sigma_2^2 - K_{12}^2 = \sigma_1^2\sigma_2^2(1 - \rho_{12}^2)$$

Here, $\rho_{12} = \frac{K_{12}}{\sigma_1\sigma_2}$ is an indicator of the interconnection between the noise component counts of the two branches at the same time interval.

Given that the table movement is identical for all of its components, we represent the multiloop probability density function of gradient n:

$$w(n) = \frac{1}{\sqrt{(2\pi)^{2N} det(\Sigma)}} exp\left(\frac{-1}{2} n^T \Sigma^{-1} n\right) = \prod_{q=1}^{N} \frac{1}{\sqrt{(2\pi)^2 det(K)}} exp\left(\frac{-1}{2}(n(q))^T K^{-1} n(q)\right) = \prod_{q=1}^{N} w(n(q)) \quad (10)$$

Therefore, we express the joint probability density $w(n)$ of the counts of the noise component of the 1st cardiac period recorded over the two branches of the electrical cardiac impulse through $w(n(q))$:

$$w(n(q)) = \frac{1}{\sqrt{(2\pi)^2 det(K)}} exp\left(\frac{-1}{2} n^T K^{-1} n\right) = \frac{1}{\sqrt{(2\pi)^2 det(K)}} exp\left(\frac{-1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2} n^{\langle i\rangle}(q) k_{ij} n^{\langle j\rangle}(q)\right) \quad (11)$$

Let us represent the component k_{ij} of table K^{-1}, which is the opposite of table K:

$$K^{-1} = \frac{adj(K)^T}{det(K)}$$

where, $adj(K)$ is a consolidated table:

$$adj(K) = \begin{pmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{pmatrix}$$

Here, k_{ij} is an annex to the initial table:

$$k_{11} = \sigma_2^2 \quad k_{12} = -K_{21}$$
$$k_{21} = -K_{12} \quad k_{22} = \sigma_1^2$$

The opposite table K^{-1} corresponds to the following expression:

$$K^{-1} = \frac{adj(K)^T}{det(K)} = \frac{1}{\sigma_1^2\sigma_2^2 - K_{12}^2}\begin{pmatrix} \sigma_2^2 & -K_{12} \\ -K_{21} & \sigma_1^2 \end{pmatrix} = \frac{1}{\sigma_1\sigma_2 - (1-\rho_{12}^2)}\begin{pmatrix} \frac{\sigma_2}{\sigma_1} & -\rho_{12} \\ -\rho_{21} & \frac{\sigma_1}{\sigma_2} \end{pmatrix} \quad (12)$$

Applying the simulation represented by M cardiac periods, we express the probability density of the counts of the interfering component on the branches of the electrical cardiac impulse as $w(n, M) = \prod_{k=1}^{M} w_k(n)$. In this case, $w_k(n)$ is the density probability of the gradient n.

A closer assessment of the changes in the most informative electrical cardiac impulse revealed that the magnitude of the ST segment shift also changes when the current phase of the IHD is recorded on the branches of the electrical cardiac impulse.

The process of ventricular polarity recovery changes when blood flow deteriorates in some areas of the heart. Simultaneously, further IHD progression showed a synchronous change in the ST segment configuration in the neighboring branches of the electrical cardiac impulse (Fig. 5).

When necrosis occurred, splitting of the ST segment was observed (Fig. 6) and ST elevation was recorded as it progressed (Fig. 7).

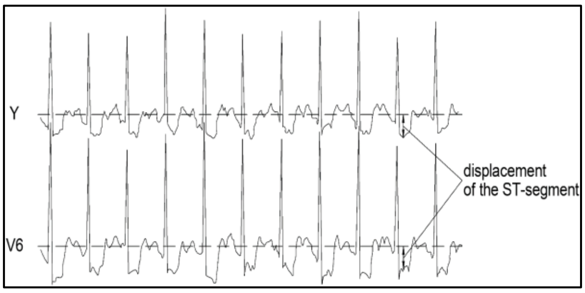

Fig. 5: External view of multichannel registration of electrical cardiac impulse where ST segment shift in neighboring branches is noted

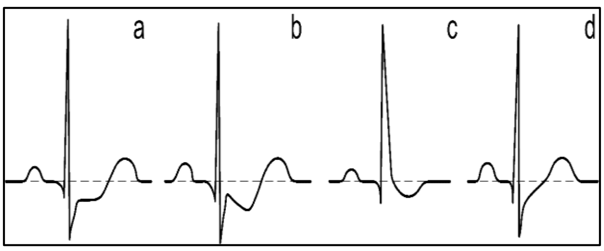

Fig. 6: External view of ST segment depressions

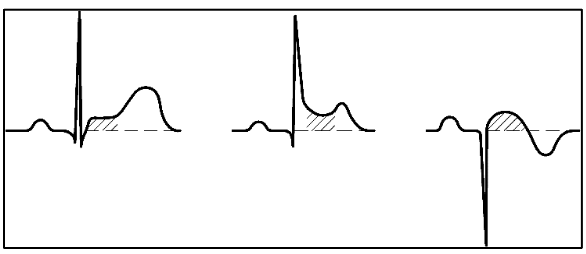

Fig. 7: External view of ST segment elevations

The following polynomial expresses the simulation of the k-th ST sectors of i^{th} branch $S_{ST_k}^{\langle i \rangle}(t)$:

$$S_{ST_k}^{\langle i \rangle}(q) = b_{2,k}q^2 + b_{1,k}q + b_{0,k}, q = 1,2,\dots,N$$

At a definite phase of IHD, a function of IHD progression from the value of the ST-segment shift in neighboring branches is formed. Consequently, we applied a simulation that described the change in the electrical cardiac impulse within the ST segment:

$$b_{2,k} = b_2 + k\Delta b_2$$

$$b_{1,k} = b_{1,k} + k\Delta b_1 \qquad (13)$$

$$b_{0,k} = b_{0,k} + k\Delta b_0$$

where, b_2, b_1, b_0 are unchanged components of polynomial indices; $\Delta b_2, \Delta b_1, \Delta b_0$ are values describing the change in polynomial indices during the 1st beating of the heart muscle during IHD and k is the index of the cardiac period starting at the ST-segment shift. Figure (8) shows the algorithm scheme for detecting myocardial ischemia. In the context of cardiac cycles, myographic interference is extracted based on an estimation of the true cardiac cycle shape. This facilitates the adaptation of the proposed model to diverse ECG signals from patients.

The following formula was proposed to obtain the threshold value for the ST segment, which determines whether the patient has ischemia:

$$Z = \sum_{k=1}^{M} \sum_{q=1}^{N_k} \sum_{i=1}^{2} I_{k,i}(y_{ST_k}^{\langle i \rangle}(q) - \hat{S}_{d_K}^{\langle i \rangle}(q)) \qquad (14)$$

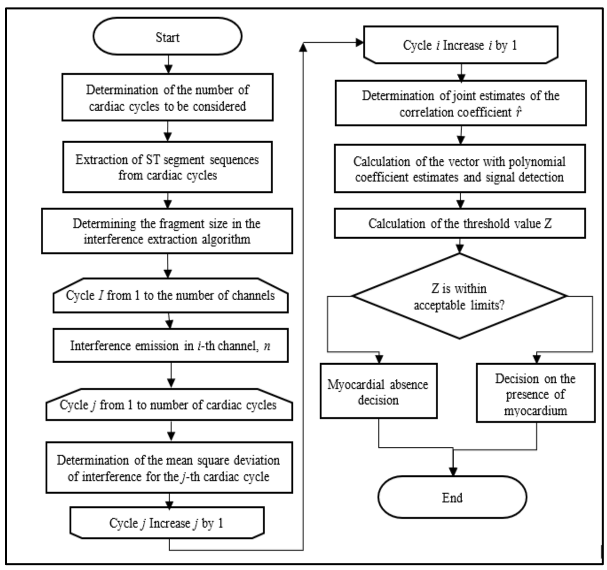

Fig. 8: Myocardial ischemia detection algorithm

DOI: 10.3844/jcssp.2025.1003.1014

Results

This study created a methodology for the multistage simulation of the electrical cardiac impulse. It forms the basis of an ordered chain of operations for recognizing IHD phases by examining the multichannel registrations of the electrical cardiac impulse that is resistant to the interfering component. The simulation describes the change in the electrical cardiac impulse within the ST segment during the progression or next phase of IHD.

To test the proposed methodology, data were obtained from the European ST-T database (Taddei *et al*., 1992), total 140 screen images were obtained and tested using the proposed algorithm. This database has been demonstrated to be a valuable tool for evaluating ambulatory ECG monitoring systems, offering a comprehensive set of metrics for analysis. The database encompasses a wide range of information, including ST segment (ST) and T-wave (T) alterations, along with onset, offset and peak beats. In addition, it provides detailed annotations of the QRS, beat types, rhythm and signal quality variations. A total of 372 ST and 423 T changes were documented in the recordings, making it a valuable resource for researchers in this field. The subjects were 70 men aged 30-84 years and eight women aged 55-71 years. Table (4) shows the results of the proposed methodology compared with those of other algorithms using binary sensitivity and specificity assessments, presenting the proposed method under the first number.

The simulation provides automatic interference-resistant detection of IHD phases in sections of the electrical cardiac impulse exposed to significant noise, for example, when performing the registration shown in Fig. (9).

It is evident that the study did not consider atypical ECG signals or cardiac conditions as experiential data. Consequently, this is one of the limitations when measuring the performance of the proposed algorithm in patients with these types of diseases.

Thus, the results obtained in this study can be useful for further improving methods and algorithms for processing and analyzing polymodal biomedical data, which is relevant for improving systems for supporting medical diagnostic decision-making in medical information systems (Gorelov *et al*., 2020; Alexandrov *et al*., 2022; Lampezhev *et al*., 2021).

Table 4: Comparison of algorithm performance in detecting myocardial ischemia

No	Sensitivity %	Specificity %	Reference
1	91.5	92.9	This study
2	89.7	94.6	Liu *et al*. (2021)
3	90.3	87.9	Wang *et al*. (2016)
4	91	85	Sun *et al*. (2012)

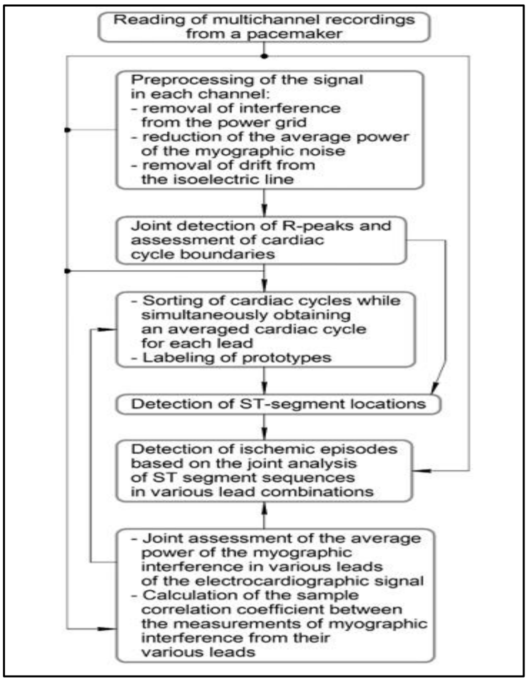

Fig. 9: External view of the automatic interference-resistant detection of IHD phases in significantly noise-prone segments of an electrical cardiac impulse

Discussion

This article presents a novel solution to modelling interference-resistant processing of multichannel ST segment ECG recordings for preliminary diagnosis of ischemia stages of cardiac muscle. The findings of the study suggest that the intervention created could successfully reduce the impact of muscle noise interference, which is crucial for improving diagnostic results in practice. The majority of interference-resistant solutions are characterized by wave transformations or processing through neural networks. In contrast, the proposed solution relies purely on polynomial approximation of multiple short segments of lead ECGs, providing a superior assessment of the "true" signal despite a broader array of descriptions with broadband noise aspects. The sensitivity and specificity of 91.5 and 92.9%, respectively, are consistent with the findings of Liu *et al*. (2021) and surpass those of Wang *et al*. (2016); Sun *et al*. (2012) for nearly all other assessments. This suggests that the proposed method is effective in assessing the variability of ST segment features, which is essential for rapid diagnosis and the prevention of further ischemic development. The emphasis on establishing the connection of noise components between channels is particularly noteworthy, as it ensures accurate assessment of ECG parameters and renders the algorithm less susceptible to variances in signal quality from prolonged registration. When considered in conjunction with other machine learning systems, this advancement has the potential to enhance diagnostic accuracy and broaden the feasibility of its application in automated systems that support clinical decision-making.

Conclusion

To create a technique capable of automatically recognizing IHD phases, it is essential to apply a multistage simulation that describes the change in the electrical cardiac impulse, considers the change in the recorded impulse during the progression of the IHD phases and is robust to the influence of interfering components in different branches of the electrical cardiac impulse. The methodological approach proposed in this study makes it possible to develop an effective solution for this problem.

This is confirmed by the results of experiments on the confirmation or non-confirmation of the IHD phase using test and archived electrocardiosignals. The level of reliability of the data obtained in the results compared to the proposed methods reached p = 96%. In a consortium with I.M. Sechenov first Moscow State Medical University as part of a world-class research center, it was found that the difference between practical data and theoretical data was less than 5%.

Robust ML models rely on the availability of sufficient, accurate data. Consequently, a potential avenue for enhancing the efficacy of the proposed algorithm involves its integration with machine learning systems, with the objective of enhancing the accuracy of detecting myocardial infarction.

Acknowledgment

Thank you to the publisher for their support in the publication of this research article. We are grateful for the resources and platform provided by the publisher, which have enabled us to share our findings with a wider audience. We appreciate the efforts of the editorial team in reviewing and editing our work, and we are thankful for the opportunity to contribute to the field of research through this publication.

Funding Information

The findings of this study were obtained under the Grant Agreement in the form of subsidies from the federal budget of the Russian Federation for state support for the establishment and development of world-class scientific centers performing R and D in priority areas of scientific and technological development No. 075-15-2022-307 dated April 20, 2022.

Author’s Contributions

All authors made a significant contribution to the preparation, development and publication of this manuscript.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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