

Algorithmization of Electrostatic Model for Solving the Direct Problem of Electrography

Tagirbek Gaidarbekovich Aslanov, Naur Zamirovich Ivanov, Shamil Shamil'evich Anudinov and Tatiana Vladimirovna Karlova

World-Class Scientific Center "Digital Biodesign and Personalized Healthcare", Institute of Design and Technology Informatics, Russian Academy of Sciences, Vadkovsky Lane, 18, Building 1A, Moscow, Russia

Article history

Received: 19-11-2024

Revised: 21-01-2025

Accepted: 29-01-2025

Corresponding Author:
Tatiana Vladimirovna Karlova
World-Class Scientific Center
"Digital Biodesign and
Personalized Healthcare",
Institute of Design and
Technology Informatics,
Russian Academy of Sciences,
Vadkovsky Lane, 18, Building
1A, Moscow, Russia
Email: tatiana.v.karlova@yandex.ru

Abstract: An analysis of the creation and implementation of algorithms to control cardiological processes occurring in the cardiovascular system using software and hardware diagnostic systems is a required activity. This study considers ways to improve the methods of medical data processing using electronic diagnostic systems, relying on existing methods of mathematical simulation of human body states. This study describes the development of a method that solves the direct problem of electrical cardiography by using complete electrostatic simulations. For this purpose, the selection of key characteristics of simulations of anatomical features and physiology of an organism is used by considering the bioelectrical data obtained experimentally. This study describes the basic relations to characterize the electric field and considers the electrophysical properties of biological tissues. The simulation considered the specifics of the functioning of the proposed method, which imitates the activity of the heart muscle. A novel algorithm is proposed that allows for the detection of myocardial pathological changes that arise during diagnostic procedures, utilizing the reconstructed trajectory of single charge movement. An in-depth study of the electric fields of the controlled object using multipole dispersions was conducted, and the impact of the level of multipole dispersions on the reliability and error of the simulation results was analyzed. The proposed simulation does improve the reliability of the parameters obtained during diagnosis using electronic cardiac systems. The implementation of calculation methods for electrophysiological signals based on this model has the potential to facilitate diagnostic procedures even in the presence of undetected pathologies, offering a valuable complement to traditional diagnostic techniques.

Keywords: Cardiology, Electrocardiography, Hardware-Software Diagnostics, Direct Problem of Cardiography, Electrostatic Simulation

Introduction

One of the most pressing medical problems is the development of a range of diagnostic techniques to reduce the percentage of disabilities and fatalities among people. Moreover, this problem is relevant for different states. A potential solution to this problem is the introduction of various automated systems that can monitor the state of the cardiovascular system.

Modern electrocardiographic studies are based on a specific myocardium model as an electrical system for approximate field descriptions. The dipole projects the recorded leads onto the currents on the sides of Eithoven's triangles (Huda *et al.*, 2020; Raziman *et al.*, 2019). A large

assortment of diagnostic techniques contains base analytical forms of the curves fixed by the electrocardiographic equipment of the leads (Faust *et al.*, 2021; Ho and Ding, 2022; Xie *et al.*, 2020; Maturo and Verde, 2022).

It is difficult to adjust the necessary parameters of the presented models according to diagnostics because the number of available parameters significantly exceeds the number of recorded signals (Kolawole *et al.*, 2023). The described disadvantage is characteristic of the dipole-based heart model because, neglecting the parameters of the sphere of propagation of the electrically active potential, the presented model includes six levels of freedom, and only three signals are linearly independent in the set of leads. Other processing information

techniques in cardiac research aim to optimize the visual display of graphical data presented to a specialized doctor for independent analysis of Electrocardiogram (ECG) and further formation of a diagnostic epicrisis (Brunzini *et al.*, 2023; Mayinger *et al.*, 2023).

According to statistical data, there are noticeable differences between the confirmed number of models performing the ECG pulse restoration of actual characteristics of current algorithms and imaginative modifications involved in forming a conclusion about the conducted diagnostics. The first type of the described models has some lag, justified by the complexity of the experimental search for a set of model parameters. The first type of model is closer to the actual processes occurring in the myocardium; therefore, it provides a complete diagnostic picture.

The optimization and automation of research systems have led to new effective research techniques that can solve many essential problems. The most widespread systems in recent times are those that guarantee long-term continuous monitoring of aspects of the body's functioning. These include devices that monitor heart rhythm, heart rate, etc., (Ip, 2019). The parameters of heart function reflect its functionality in the form of studies and the functioning of most body systems. With the help of timely studies, it is possible to prevent sudden death, even in the asymptomatic course of the disease. Objective assessment of the patient's current state involves cardiac research systems, which increase the reliability of recognizing pathologies through the competent application of resuscitative measures. The equipment of diagnostic systems is significantly expanding, which helps doctors anticipate further development of the disease and prepare a treatment protocol in advance.

The primary task of ECG monitoring, which occurs automatically in the ward monitoring systems in the cardiology field in the diagnosis of arrhythmia, is considered to be the qualitative recognition of the most dangerous abnormalities of heart rhythm (Sahoo *et al.*, 2020) that largely predetermines the qualitative functioning of the automation system. It is reasonable to pay increased attention to the issue of identifying cardiac abnormalities. Monitoring spectrum features is essential when working in an environment of arrhythmia signs and other pathologies in the cardiovascular system. The task of selecting the signal frequency description is critical for system optimization in the process of patient monitoring and requires the development of efficient techniques for electrocardio signal processing.

Among the most essential issues in disease automation in cardiology, we can refer to a range of research necessary for modern medicine. Arrhythmia symptom search systems with chaotic variations of cardiac cycle durations (in other words, one of the forms of atrial fibrillation) require weighted practical solutions

(Tyapkin *et al.*, 2016; Ahmed & Zhu, 2020). Special attention in electrocardiosignal processing should be paid to the suppression of interference reflected in the results of electrocardiosignal monitoring and searching for heart rhythm abnormalities (Kuklin *et al.*, 2024). The solution to this problem becomes possible with large-scale numerical resources of modernized technical means, helping move to complex and efficient preprocessing procedures.

This study examines the impact of the number of decomposition terms on the accuracy indices used to describe potential fields. A detailed examination of the heart as a discrete entity is provided to elucidate the projections of the evolving model. Subsequently, an algorithm was developed to address the issue of direct electrocardiography and to facilitate the detection of dangerous cardiac pathologies.

The main purpose of this study is to improve the methods that provide computerized processing of medical information obtained by electronic diagnostic systems and interpretation of electrical cardiographic data due to electrical cardiogram simulations by the methods under consideration. These methods absorb the main advantages of systematized simulations and simulations based on the analysis of current bioprocesses, which are the basis of generated electrical cardiac impulses.

Literature Review

The optimal functioning of the heart is due to the contractions of various parts of the myocardium in a specific sequence based on electrical pulses. Of course, the primary heart function is to work as a pump, although it is worth understanding that the contraction mechanism of the various ventricles and muscles is extremely complex.

If the main characteristics of the myocardium are considered, the principles of its function should be used. Thus, specialists should have a clear idea that myocardial fibres are not continuous in nature; upon detailed examination, it becomes noticeable that the myocardial fibres are a set of cells, each approximately 100 μm long, adjacent to each other (Heusch, 2020).

It is important to note that each cell is surrounded by a special plasma membrane consisting of three layers, each approximately 7-8 nm thick. The outer and inner layers consist of specific protein molecules arranged in a single row, while the middle layer contains a biomolecular layer of lipids.

Further, we should consider the transmembrane resting potential, which describes the potential difference between the inner and outer parts of the membrane. In most cases, this parameter is equal to 90 mV. This implies an extremely strong depolarization of the existing potential. Upon completion, the criterion returns to its original value.

Conductive scaffolds are of significant value in the construction of functional myocardial tissues and the promotion of tissue reconstruction in the treatment of myocardial infarction. An electroactive engineered cardiac patch has been demonstrated to effectively improve left ventricular remodelling and restore cardiac functions, including ejection function. Furthermore, it has been shown to improve the propagation of electrical pulses and promote the synchronous contraction of cardiomyocytes in the scar area with normal myocardium, effectively reducing the susceptibility of myocardial infarction rats to arrhythmias.

Microtopography is another essential criterion that significantly influences the formation of specific electrophysiological signals (Sands *et al.*, 2024). In recent years, researchers have developed a complete picture of the main features of this process. Its essence lies in the extremely specific geometry of the heart, localization of the bundle of Hiss and its branching (Boonstra *et al.*, 2022). Simultaneously, it is worth paying attention to the speed of the excitation propagation through the myocardium. A separate feature here is that the spread of excitation had nothing to do with the anatomical course of the muscle fibres. In this case, the specific excitation time of the peripheral endings within the conduction system is the determining factor. An equally important parameter is the thickness of the heart wall. To determine the half-diameters of the region in the current time segment at time t , we can use the relation:

$$R = v_M(t - t_0) \quad (1)$$

Here, v_M is the value of the rate of development of excitations in cardiac muscle, and t_0 is the duration of excitations characterized by the ending of Purkinje's fibres.

Consequently, the key principle for ECG development is the combination of various electrochemical, anatomical and microbiological factors, which in most cases do not have an accurate mathematical description. As a result, the process of forming a model with the help of which it was possible to give the most accurate description of the processes within the human heart is greatly complicated.

The essential task of medical automated equipment is to improve existing diagnostic capabilities. Such activities must consider the objective requirements of the main features of the diagnostic process and the specific working conditions.

It was suggested that it would be more promising to use computers programmed to implement a specific logic for diagnostic examination to automate the diagnostic process. The main advantages of this category of devices are the presence of a particular electronic memory and the fact that they can use different flexible programs that operate with a vast number of diagnostic algorithms.

Breathing is a factor to consider when generating a cardiogram because it causes heart rate deviations of

10%. Therefore, it is essential to organize data collection at specific intervals where it is possible to ignore these distortions.

Researchers have developed many mathematical techniques to assess diagnostic efficiency and investigate and diagnose various disorders. Of great importance is the use of a range of specific computational devices that use special formalized physician diagnostic features or cybernetic algorithms for data selection (Alexandrov *et al.*, 2023a). Simultaneously, the generated solutions coincide with the traditional medical empirical approach.

The simulation of the heart muscle function as a source of specific physiological oscillations can also be used in practice. The purpose of the simulation was to develop an actual complex capable of producing a package of information about a patient, thus creating new relevant data about that complex. This system can be used to validate various theories. Simultaneously, it is also necessary to remember that with the help of such a model, it is possible to provide sufficient clarity in interpreting various measured values. This significantly increases the effectiveness of the methodology and expands its applications. Consequently, based on the aforementioned principles, we can conclude that using the model approach provides a justified way to solve the diagnostic problem in electrocardiography, which will contribute to achieving optimal solutions to existing problems.

Figure (1) describes in more detail the specific sequence of the main simulation steps, which makes it possible to reflect the most qualitative situations in the process under study.

By analyzing the image, it is possible to obtain all the necessary information about the features of the study stages that significantly clarify the features of the particular algorithm functioning.

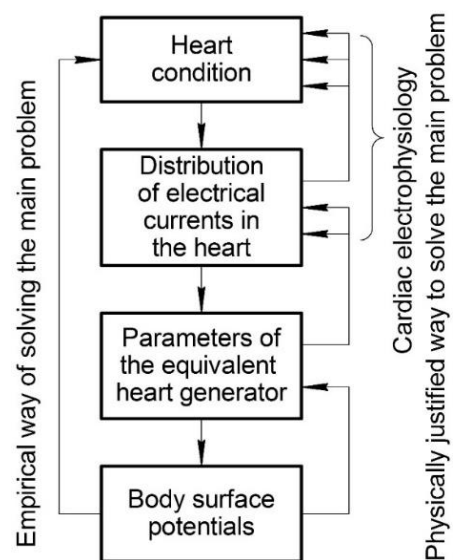


Fig. 1: Methods for solving electrocardiographic problems

It is worth noting that in practice when solving diagnostic problems, it is essential to refuse actual descriptions of a particular object and to use approximate models that characterize only a specific part of the properties. Using actual object descriptions implies the necessity of creating incredibly complex formulas, which will contain an enormous number of variables. Simultaneously, the models focus only on the necessary information to allow us to find a solution to the set tasks without significant loss in the accuracy of the solution (Alexandrov *et al.*, 2023b).

One method for obtaining a diagnosis from ECG is the use of machine learning. For example, there is a method for diagnosing patients with occlusive myocardial infarction and no ST-segment elevation on baseline electrocardiogram. Few experienced physicians have sufficient pattern recognition skills; therefore, many patients with this condition do not receive timely assistance. Machine learning is good for solving many problems in interpreting 12-lead ECGs because myocardial ischemic distortions for each lead have a dynamic relationship between leads (Al-Zaiti *et al.*, 2023).

Artificial Intelligence (AI) is rapidly advancing in medical technology, especially in the field of image analysis. ECG diagnosis is an image analysis technique in which cardiologists evaluate the waveforms presented in a 2D image. Developments based on convolutional neural networks can efficiently recognize images and patterns from ECG. Deep learning with a simple convolutional neural network architecture derived from even a small ECG database can provide an advantage or at least be as good as cardiologists in recognizing myocardial infarction. Such technology can be effectively used as a first-line triage and assessment tool to assist in final clinical diagnosis (Makimoto *et al.*, 2020).

Deep learning is a promising method for analyzing data obtained through ECG. Deep learning models, particularly those using convolutional neural networks, have surpassed rule-based and other machine-learning models. Deep learning is a promising method for analyzing resting ECG signals to detect structural cardiac abnormalities. It has clinical applications for better screening of asymptomatic populations and accelerating the diagnosis of symptomatic patients at risk for cardiovascular diseases. Models based on deep learning exhibit a high degree of specificity although low sensitivity (Al Hinai *et al.*, 2021).

Considering these factors, we can conclude that the issues related to establishing the degree of relationship between the characteristics of the source, its structure and the distribution of electrical current in the heart muscle are currently understudied. As a result, the search for a solution to the problem related to the determination of specific parameters of the equivalent generator is an extremely expedient solution. This task is inherently intermediate, but

its successful solution will contribute to the rapid development of the industry under consideration.

At the present stage, because of the level of functional capabilities of devices described in the scientific literature, with the help of which the condition of the human cardiovascular system is monitored, it is impossible to talk about a sufficiently acceptable level of automatic and semi-automatic diagnosis. Insufficient attention has been paid to the mathematical support of the diagnostic processes. In particular, there is a shortage of studies that consider the process of ECG genesis simulation. Existing research papers mainly consider the issue of increasing the resistance to interference of existing processing methods to improve the accuracy of the results. However, almost no studies have considered the problems in the field of automated detection of various pathologies.

Materials and Methods

It is imperative to deliberate on the characteristics of the solution to the issue of modelling the electrical activity of the heart, in addition to the algorithmic implementation of said solution. Specifically, the method of analyzing the electric field of the control object using multipole decomposition. The research conducted has resulted in the proposal of an algorithm for modelling the electric field of the heart, as well as the justification of the methods of determining the parameters of the developed model. It is imperative to delineate the limitations and capabilities of the developed model and deliberate its applicability for ECG analysis.

First, we should understand in detail the electrical activity of the heart muscle, relying on the convergent series of multipole intervals (Lea *et al.*, 2022). This approach was developed based on existing ideas regarding the heart as a definitely distributed electrical generator. It is worth noting that, despite considerable mathematical elegance, in practice, this approach was sporadic for the following reasons:

- This approach is completely incomprehensible in the absence of a serious mathematical background.
- Obtaining the components of the multipole series requires extremely complex calculations.
- Despite the high complexity of this methodology, it does not demonstrate a significant advantage in terms of diagnostic accuracy and is impractical, as it requires a large number of resources to obtain the same results owing to simpler techniques.

In essence, the multipole expansion of the potential acts as an infinite series, where the terms of the series are inversely proportional to the degree of distance and the origin of the coordinates. Such an expansion acts as a canonical representation of the surface distribution of the

potential, using monopole, dipole, tripole and a set of higher-order charges.

Owing to the volume distribution of the current sources, it is possible to create a field whose potential is described by the following formula:

$$V(\vec{r}) = \frac{1}{4\pi\gamma} \int_{V'} \frac{-\nabla J(\vec{r}')}{|\vec{r}-\vec{r}'|} dv \quad (2)$$

Where γ is the total specific electrical conductivity of the medium ($\text{Om}^{-1} \cdot \text{m}^{-1}$), \vec{r}' is the radius vector drawn from an arbitrarily chosen origin of coordinates to some point in the distribution area of sources V' , and \vec{r} is the radius vector connecting the origin of coordinates with the observation point.

To make the reasoning more general and universal, we propose replacing delta J with an equivalent value used in field theory.

After the decomposition of expression (1), it takes the following form:

$$V = V_0 + V_1 + \dots + V_N + \dots$$

Figure (2) shows the coordinate space for a similar environment in detail.

$$V_0(\vec{r}) = \frac{1}{4\pi\gamma r} \int_{V'} \rho(\vec{r}') dv$$

Further transformations bring the formula to the form:

$$V_1(\vec{r}) = \frac{\vec{r}\vec{d}}{4\pi\gamma r^3} \quad (3)$$

Where:

$$\vec{d} = \int_{V'} \rho(\vec{r}') \vec{r}' dv \quad (4)$$

When the systems are composed only of several equivalent current generators with different potentials, the relations proposed in (2) and (3) are identical to expressions describing the magnitudes of the dipoles and dipole moments. Consequently, the use of such formulas allows us to evaluate the contribution of a particular dipole moment to the total potential. In other words, the intensity of the dipole term within the multipole decomposition is obtained.

If there is a shift in the origin of the coordinates by some vector, the dipole moment takes the following form:

$$\Delta \vec{d} = \vec{b} \int_{V'} \rho(\vec{r}') dv$$

It is necessary to consider the dipole term from the viewpoint of potential decomposition:

$$\frac{\partial^2}{\partial x_i \partial x_j} \frac{1}{r} = \frac{1}{r^5} (3x_i x_j - r^2 \delta_{ij})$$

Thus:

$$V_2 = \frac{1}{8\pi\gamma r^5} \sum_{i=1}^3 \sum_{j=1}^3 x_i x_j Q_{ij}$$

where:

$$Q_{ij} = \int_{V'} \rho(\vec{r}') (3x'_i x'_j - r'^2 \delta_{ij}) dv$$

In the following set of quantities, Q_{ij} will act as the quadrupole moment tensor.

Further, a resulting expression is necessary to describe the total potential of the electrocardiographic field:

$$V(\vec{r}') = \frac{1}{4\pi\gamma r} \left[\frac{1}{r} \int_{V'} \rho(\vec{r}') dv + \frac{\vec{r}}{r^3} \int_{V'} \rho(\vec{r}') \vec{r}' dv + \frac{1}{2r^5} \sum_{i=1}^3 \sum_{j=1}^3 x_i x_j \int_{V'} \rho(\vec{r}') (3x'_i x'_j - r'^2 \delta_{ij}) dv \right] + \dots \quad (5)$$

Based on this formula, we find that the capabilities of quadrupoles will decrease in proportion to distance, and the degree of decrease of the latter will be greater than that observed for dipoles and unipoles.

Peculiarities of Determining the Degree of Influence of the Number of Decomposition Terms on the Accuracy Rates of Potential Field Descriptions

In Eq. (5), the first integral is used to obtain the total current that enters and leaves the integration region. Therefore, we can conclude that unipolar components will allow us to build the final dependence describing the electrical activity of each significant point source reflecting the current processes of the organism functioning. Simultaneously, the calculation of the second antiderivative will help establish a gradient reflecting the ranking of the current components.

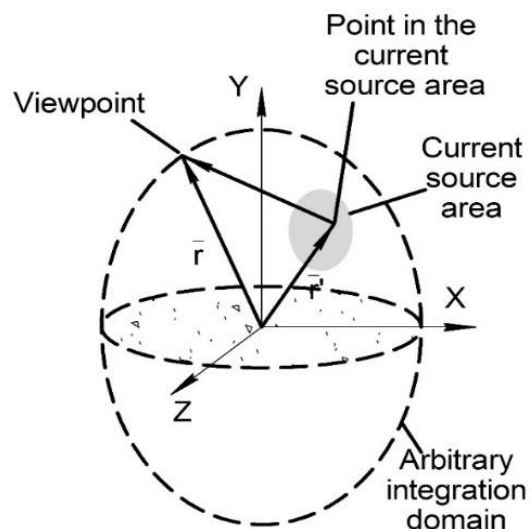


Fig. 2: Coordinate space of homogeneous conducting medium

If we integrate over the value V' , which includes all current sources and express the result as a spatial rather than unidirectional moment, a sequence of components will be formed, a part of the third term of the equation. Their totality provides a peculiar quadrupole tensor to characterize the distribution of the current dipoles.

In a situation where the system consists of one dipole at the origin of the coordinates, the numerical value of the quadrupole term of the expansion is zero. The reverse displacements lead to the opposite situation. Thus, the representation of the actual distribution of dipoles can be formed by placing such single dipoles, characterized by absolute values and orientations, at some displaced points of the field region. It is necessary to select the locations of the displaced dipoles to provide an optimal approximation of the five key distributed components.

When some system will not be electrically neutral, we can use the relation:

$$\int_V \rho(\vec{r}') dv \neq 0 \quad (6)$$

It turns out that it is not worth applying higher-order dipoles and multipoles in studies of electrical activities of distributed sources because, within such a formulation, the value of the first summand will be much larger than the values of all the following summands.

The simplification of all performed reasoning requires the use of the electrostatic analogy method. The most important advantage of this approach is that it simplifies reasoning considerably without violating its generality.

If we consider the general case, we should realize that replacing the dipole with a single electric charge with equivalent characteristics is impossible under the existing electrostatic conditions. From a mathematical viewpoint, this implies that a particular system of equations to describe the equivalent substitution will not have a solution. This problem is solved by introducing additional conditions characteristic of electrocardiography, which make a significant difference. First, the measurement of electrocardiographic biopotential values will occur at some fixed points, and there is a restriction on the total number of such points. Another characteristic feature of electrocardiography is that it measures the potential difference rather than the potentials themselves. As a result, if we consider all the above mentioned characteristic features, we can obtain a model of the electrical activity of the heart, which has a physical justification. Thus, we can conclude that lowering the highest term of the multipole decomposition of the heart electrical activity can occur if an equivalent replacement of the dipole with a single charge, whose characteristic features will be time-varying magnitude and coordinates, is performed.

In this case, a single electrostatic charge forms a potential that can be calculated using the following formula:

$$V = \frac{q}{4\pi\epsilon\epsilon_0 r} \quad (7)$$

For an electric dipole, an expression of the following form is valid:

$$V = \frac{\vec{r}\vec{d}}{4\pi\epsilon\epsilon_0 r^3} \quad (8)$$

Where \vec{r} is a vector from the dipole centre to the observation point, and \vec{d} is a vector of the dipole moment.

By transforming expression (8), we can obtain the following formula:

$$V = \frac{q}{4\pi\epsilon\epsilon_0 r^2} \vec{n}\vec{l}$$

Where \vec{n} is a unit vector with direction to the observation point, and \vec{l} is a vector between the negative and positive poles of the dipole.

However, it is worth understanding that registering the potential formed by the electric field source within an arbitrary point in space is theoretically possible. However, in practice, within the framework of electrocardiology, it is possible to record the potential difference using appropriate measuring equipment. In this case, as an example, we must consider two points of space, A and B. To determine the potential difference between the points under consideration, the following formula is necessary:

$$V_{B-A} = \frac{q}{4\pi\epsilon\epsilon_0 r^2} \left(\frac{1}{r_B} - \frac{1}{r_A} \right)$$

To determine the total potential difference between the points created by the electric dipole, the following expression must be used:

$$V_{B-A} = \frac{q}{4\pi\epsilon\epsilon_0 r^2} \vec{l}(\vec{n}_B - \vec{n}_A) \quad (9)$$

Figure (3) shows a flat model in more detail, which makes it possible to provide a conditional combination of the two situations under consideration. Here, C is the location of the unit's electric charges.

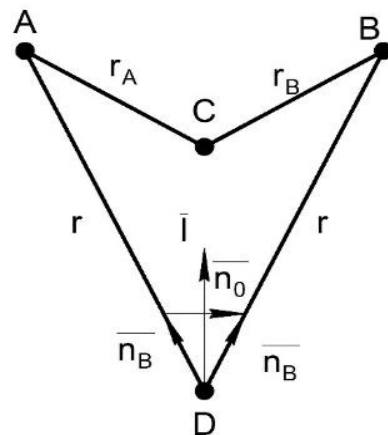


Fig. 3: External view of the flat model

In the particular case when $V_A = V_B$, the distances from the point source to points A and B must equal each other. The analogous situation for an electric dipole corresponds to the case when the difference vector \vec{n}_B and \vec{n}_A and vector \vec{l} are perpendicular.

Then, it is necessary to hypothesize that the vector turns clockwise, which means that it has decreased by ΔV_A and will increase by ΔV_B . As a result, a positive potential difference was formed.

If a transition from the study of a qualitative model to the development of point quantitative descriptions of the effects under consideration is necessary, a more detailed consideration of the issue related to the determination of the number of parameters to form an unambiguous representation for a particular source of electric potential is required.

Before proceeding, we should remark that Eqs. (5-6) and any other expressions used to describe the multipole decomposition potential can be represented in the form:

$$V = f(a_1, a_1 \dots a_n)$$

Within the framework of studies in this industry, there is a thesis that an arbitrary electric dipole is uniquely characterized by six parameters. In this connection, a system describing the dipole should contain at least six equations. The solution of such a system requires information about the exact values of the potentials at different points, whose total number is always numerically equal to the number of equations.

To describe an arbitrary unit electric charge, three spatial coordinates and the value of the electric charge will be sufficient; that is, four parameters will be sufficient. Thus, it follows that a system of four equations is sufficient.

During mathematical simulations, we established that the movement routes of unit charges can be fixed owing to the routes of movement of the ends of dipole moment vectors being identical to dipoles. Thus, it is possible to describe the picture for several points and confirm the replacement of dipole models with unipole ones.

Analysis of the Heart Muscle Model as a Single Point Charge Fluctuating in Time and Space

If we study the functioning of the heart muscle as a mobile point charge, we should realize that such a representation acts as a zero-order approximation for the Gabor-Nelson model. While the heart typically functions as a distributed rather than a point source of the electric field, it is feasible to delineate an approximate point of reference for which the unipole (single-charge) term of the aforementioned expansion offers the most accurate approximation of the electric potential at the designated observation points, which we may designate as the "electric center" of the heart. The geometric location of the moving electric centre is represented by a closed curve, or trajectory,

within the heart. This trajectory, along with the value of the equivalent electric charge at each point along it, provides insight into the propagation of excitation and recovery processes within the myocardium. This information allows a cardiologist to reach a conclusion about the presence or absence of a pathological process in the heart tissue, its nature and its extent. This conclusion enables the cardiologist to diagnose the cardiac condition, which represents the ultimate objective of cardiac diagnosis (Vondrak and Penhaker, 2022; Gabor and Felix, 2019). Within the framework of the general case, the heart is a distributed source of an electric field. However, there is a practical possibility of establishing a point where the unipole terms of the expansion will create more effective approximations for electric potentials limited to observation points.

However, it is necessary to understand that the coordinates of such a moving electric centre can only be obtained because of the transformation of information contained within the multipoles of higher orders. Thus, if the hypothesis considered is valid, we can use the following expression:

$$V_0(\vec{r}) \gg \sum_{i=1}^{\infty} V_i(\vec{r})$$

However, it is necessary to note that at some moments of the cardiocycle, such an expression loses its validity, resulting in the sum of the higher terms for the multipole expansion being comparable to the unipole term. It is essential to understand that in such a situation, the electric centre may lose its physical meaning and appear outside the heart region.

The main problem is the insufficient number of theoretical studies of cardiac multipoles. As a result, the above interpretation of the concept is considered a hypothesis that requires theoretical and empirical confirmation.

Base Assumptions and Limitations of the Model

From the point of view of mathematical study, the full accessibility of the model always adheres to a specific simplification logic, which contributes to preserving all the main features of the modelled object. However, the essence of each feature selected as the main model parameter is quite different, depending on the specific solved problem.

Further, this study requires considering the model as a particular set of excitable units, which will generally contribute to the cellular structure of the myocardium. Owing to the technique of intracellular leads, it became possible to clarify that the monophasic action potential is the main form of bioelectric activity within a single fibre.

Next, we need to consider the membrane of an excitable cell, which, from the point of view of electrodynamics, acts as a specific closed double electric layer explained by its microscopic structure.

Homogeneity violation of the surface charge occurs during depolarization or repolarization of the cell membrane. Here, it is extremely reasonable to assume that the form of the time dependence of this potential will be similar to that of the transmembrane action potential. This statement does not contradict the basic postulates of electrophysiology.

Thus, if we summarize the definite results of the considerations related to the possibility of forming a model of ECG genesis, we can formulate a list of basic postulates that became the basis of the model and consider all introduced simplifications and limitations:

1. The fields formed using the electrical activities of the heart muscle will satisfy the requirements of quasi-stationarity, so it becomes possible to apply the methodology of electrostatic analogies.
2. The heart muscle should be studied as a unit of each myocardial cell, characterized by excitability and conduction functions.
3. The cells, whose nature should be analyzed as peculiar sources of electric fields, should be attributed to the number of elementary excitable units.
4. The membrane of a polarized cell is a looped layer of electric field. Simultaneously, the state of excitation contributes to the violation of the homogeneity of this layer.
5. The presence of transmembrane potential is the base form of electrical activity.
6. Cells can experience an excited or unexcited state
7. The geometry of the heart and conduction system determines the pattern of excitation propagation within the heart muscle thickness
8. The tissues surrounding the heart are considered an inhomogeneous anisotropic linear resistive medium
9. Potential summation will act as a way to determine the electrocardiographic lead potential

Thus, we can accept the hypothesis that the heart, from an electrical point of view, can be regarded as a distributed electrical generator consisting of a range of point sources of potential.

Application of the Created Formalized Model to Study the Processes of ECG Genesis

To implement the model practically, it is necessary to introduce discretization of the heart muscle volumes, which requires partitioning into separate elements. Their exact values determine the level of the desired detail based on the obtained electrocardiographic curves. Based on these theses, we can conclude that the recorded potential can be calculated using the following formula:

$$V(t) = \sum_{j=1}^p \sum_{i=1}^{n_j} v_{ij}(t)$$

If we consider the expression of the potential generated with the help of the first term of multipole expansion, the

density parameter of the electromagnetic field sources will be considered a constant value. Therefore, to calculate the electric field potential generated by the unipole model, the following formula is required:

$$V(t) = \frac{1}{4\pi\epsilon\epsilon_0} \sum_{i=1}^n \frac{q_i(t)}{r_i}$$

Based on the assumption (6), it can have only two values: Excited and unexcited. Based on the logic of model building, when the value is unexcited, it should be numerically equated to zero. Thus, we can conclude that the heart muscle has an excitation area with cupping of the electrified neurons at any time. To calculate the total electrical charge of the considered area, we used the ratio:

$$Q = \sum_{i=1}^{n_q} q = n_q q = \rho V' q$$

Here, n_q demonstrates the number of excited cells.

With the help of the given charged area, the potential will occur at a certain point in space:

$$V = \frac{1}{4\pi\epsilon\epsilon_0} \sum_{i=1}^{n_q} \frac{q}{r_i}$$

For the observer at point M , this system is equivalent to a single charge from an electrical perspective. In this case, this charge acts as an electrostatic analysis for the unipole term of the decomposition of the heart's electric potential. If some excited regions are symmetric, the coordinates within the formula act as centre coordinates for the symmetry of this region. Simultaneously, it is possible to confirm the existence of coincidences of the centre of gravity and the electric centre by relying on the provisions of Gauss's theorem and the principles of the analogy of electric and mechanical phenomena (Syomin *et al.*, 2022; You, 2019):

$$V(t) = \frac{1}{4\pi\epsilon\epsilon_0} \frac{Q(t)}{R_3(t)} = \frac{1}{4\pi\epsilon\epsilon_0} \frac{Q(t)}{\sqrt{[x_M - x_3(t)]^2 + [y_M - y_3(t)]^2 + [z_M - z_3(t)]^2}}$$

Variations in the exact value of the resulting charge occur because of constant changes in the specific shape and size of the excited part of the heart. However, this is not so important from the point of view of this research work because here, as in cardiology in general, the emphasis is on the potential difference. Based on this, we can conclude that the process of changing the heart charge is critical.

Formation of an Algorithm for Solving the Direct Problem of Electrocardiography

Many different approaches determine the exact parameters of equivalent electrical generator models of the heart. Some involve using the principle described in this study, namely formulating a system of equations. If the number of equations within the system exceeds the number of model parameters, the analytical or numerical solutions for the system of equations described in Eq. (8) can be used to determine their exact values.

The main advantage of this approach is its general nature; that is, it can be used to determine the various parameters of different equivalent generators. It is essential to have specific information regarding the potential difference between the number of cardiac cycle points. It is necessary to understand that such a task is sufficiently achievable under current conditions. However, it is worth noting that the main disadvantage of this approach lies in its excessively general character. This approach does not provide information about the anatomy or physiology of the heart because the system does not consider these parameters. This indicates the practical impossibility of solving vast practical problems using this system.

Thus, there is a need to develop a specific model of the electrical activity of the heart to completely exclude various output characteristics of a hypothetical cardiac generator. These characteristics were proposed only as criteria for the validity of such models. Simultaneously, this model should not act as a standard simulator of electrocardiographic curves, which implies that all existing model parameters will have a clear physical interpretation and describe heart function.

By obtaining a solution to this direct electrocardiography problem, it will be possible to create specific explanations for the genesis of various pathological ECG forms. Simultaneously, new information can be obtained for further research. Moreover, the developed mathematical model based on the existing electrophysiological and anatomical constants will contribute to determining new types of diagnostic signs and the comprehension of the main features of the physical essence of the obtained results.

As already emphasized in this research work, the primary purpose of the single-charge model is to determine the exact value of the coordinates of the electric centre and the specific centre of the electric charge. However, for practical use of this model, specific initial data are required. Here, one of the two approaches can be used, using either experimental data or mathematical simulations.

The essence of the first approach involves using an array of accumulated medical information regarding the main features of the sequence of excitation propagation within the myocardial thickness. Specific maps

characterize the microtopography of a similar process in different cardiac cross-sections. The main disadvantages of this approach are insufficient experimental data, lack of detail in the maps used for excitation propagation and lack of information corresponding to different variants of the norm and definite pathological cases.

Therefore, such factors do not allow us to fully engage in the search for solutions to the problems of simulating the electrical activity of the heart. This necessitated the development of a new approach focusing on the simulation of excitation appearance and subsequent propagation within the myocardium. The essence of this approach is the practical utilization of base regularities in this process. The basis for the practical implementation of this approach is information regarding the main properties of the heart muscle.

The most important of these is excitability because it determines all other key features of the myocardium. For example, if the excitability decreases, the heart loses its ability to generate a propagating action potential. Thus, we concluded that excitability determines the direct conductivity and contractility of the heart muscle.

If we consider one of the variants of the norm, it implies that the sinoatrial node generates an electrical pulse with a frequency of 1.0-1.4 Hz. Then, a similar excitation propagates and should get to the bundle of His, from which these electrical pulses come to the Purkinje fibres (Choquet *et al.*, 2021). The presence of the conducting system, the configuration of its features, and its location within the heart muscle will provide optimal coverage of the ventricles. Simultaneously, this process determines the efficiency of blood ejection into the aorta.

Based on existing clinical and physiological materials, it is possible to successfully solve the problem of constructing a mathematical model of the described process because, at the current stage, all the necessary information about the features and regularities of excitation propagation is available.

The first stage requires the creation of a 3D spatial model of the heart using all the existing information about the anatomy of this organ. Here, we note a characteristic feature of the discretization element when its minimum value corresponds to the cell size, whereas the required accuracy parameters determine the maximum value.

The second stage involves the construction of a specific graph describing the excitation propagation. Fig. (4) shows a fragment of the discretized structure corresponding to a real myocardium. The basis of this process is information about the basic properties of cell conductivity. At the initial moment (t_1), a cell in the sinoatrial node is excited. During the transition to the next stage, the excitation is transmitted to neighbouring elements and further transmitted to the next ones. The right side of the figure corresponds to the conducting elements of the system.

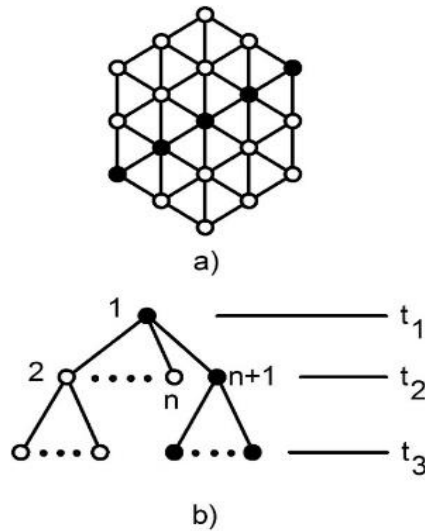


Fig. 4: Graph describing excitation propagation in the myocardium

The third stage requires the formation of a general picture to describe the excitation propagation process. In the absence of a conducting system, excitation originating in the sinoatrial node would propagate uniformly in all directions, forming a spherical excited region with the centre in the sinoatrial node and radius v_t , where v is the velocity of excitation propagation, t is the time elapsed since the onset of excitation. If the velocity of excitation propagation in the conducting system is equal to v_1 and in the contractile myocardium v_2 and $v_1 > v_2$, the shape of the excitation wavefront will be different from the spherical one. In this case, the shape of the excitation wavefront will be defined by a set of spheres with centres in the points of the conducting system and radius $-v_1(t - \tau)$. Here, τ is the time of excitation travel through the conducting system to the corresponding point, $\tau = L/v_2$, where L is the path travelled by the excitation wave through the conducting system, i.e., the length of the corresponding curve. The result will depend on the velocities v_1 and v_2 and on the configuration of the conducting system.

Note that the discreteness of the model is not considered. In addition, we point out that with the help of different shading, a conditional demonstration of the excitation wave propagation features for the selected conditions is carried out.

The practice of Using the Proposed Model in Direct ECG Genesis Problems

The conclusion regarding the relative symmetry inherent in the work of the heart as a pump can be made based on preliminary studies of the peculiarities of the heart's anatomy and the structure of its conductive system. These approximations led Einthoven to create the concept of an equilateral triangle, which acts as a system of leads in

one plane. Later, it became clear that the representation, assuming that the electric potential predominantly changes in one plane, was incorrect. This has led to additional studies aimed at solving these inaccuracies. Simultaneously, this explains why the model study focused on the adequacy of the actual ECG reproduction. Figure (5) presents a specific example of the initial stage of excitation propagation and the corresponding movements of the electrical centre of the heart. Figure (6) presents the algorithm for detecting pathology using ECG data.

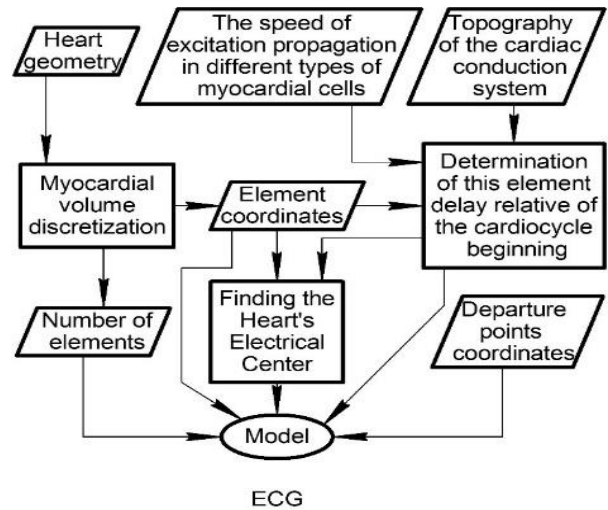


Fig. 5: Conditional flow chart of complete electrostatic model operation

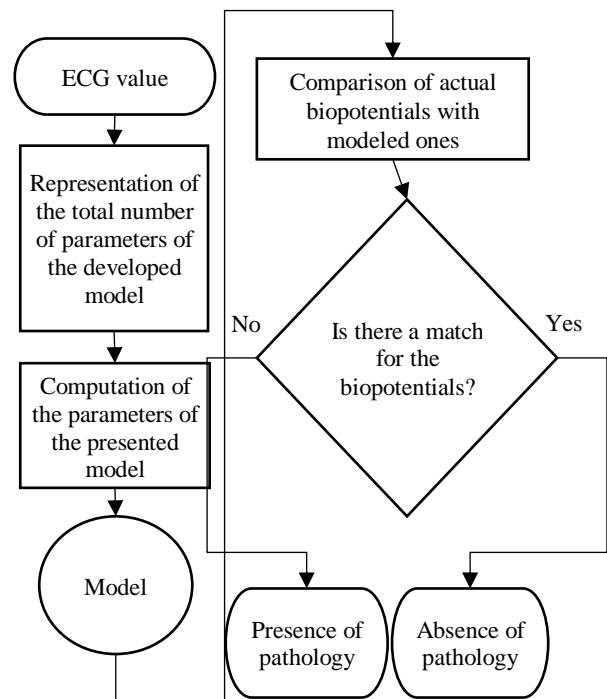


Fig. 6: Algorithm for detecting pathology using ECG data

Through the analysis of clinical practice and the literature, the interpretation of the ECG obtained using the unipole chest lead demonstrated that the most helpful characteristics are due to the exact lead numbers with the maximum amplitude and the plane of the transition zone where the characteristic ECG bend is recorded. According to the results of the conducted research, it was possible to determine that during the unipolar model usage, there would be a clear correlation between the actual and modelled ECG based on these parameters.

Results and Discussion

The opportunity to evaluate the efficacy of the proposed algorithm was presented by the I.M. Sechenov First Moscow State Medical University as part of the world-class research centre. The study of Maxwell's equations makes it possible to conclude that the algorithm for creating electrocardiological fields can have a quasi-static nature. As a result, it is possible to simplify the process of synthesis and analysis of the models under consideration because the dimensionality of the parameter matrix decreases during the calculations.

These studies confirmed the importance of considering the basic electrical properties of living tissues in terms of ECG genesis. Simultaneously, during the studies, it was possible to demonstrate that a generalized model of the conducting medium can be considered as a set of different areas with different conductivity values. These studies established the similarity between the physiological and electrical characteristics. Therefore, the set of tasks caused by diagnosing the cardiovascular system conditions transforms into selecting the necessary parameters to implement the mathematical models of the analyzed objects (Tatarakanov *et al.*, 2021).

Multicharge models are the most effective variants for solving the direct problem of simulating the bioelectrical potential formation. Studying these models demonstrated the highest adequacy of all formable results.

The first tests of the developed model based on a range of averaged physiological and morphological characteristics produced several positive results. Table (1) shows the indicators that can be achieved by the proposed model compared to the existing ones by performing pathology detection using ECG.

Studies have also shown that a simple formalized electrostatic model can replace a myocardial model based on mathematical physics. Moreover, this replacement occurs without compromising reproduction quality.

The findings may prove valuable in the development of algorithms utilized in medical information systems, as well as in the enhancement of methodologies for the analysis of biomedical data with a view to predicting the risks of cardiovascular diseases (Polezhaev *et al.*, 2023; Lampezhnev *et al.*, 2021; Gorelov *et al.*, 2020).

Table 1: Methods of detecting cardiac pathologies

| No. | Model name | Specificity, % | Sensitivity, % | Reference |
|-----|----------------|----------------|----------------|-------------------------------|
| 1 | Deep CNN | 95.8 | 91.1 | Makimoto <i>et al.</i> (2020) |
| 2 | CNN | 71 | 88 | Gupta <i>et al.</i> (2021) |
| 3 | SVM | 83.1 | 81.5 | Yao (2020) |
| 4 | CNN-LSTM | 85 | 90 | Banerjee <i>et al.</i> (2020) |
| 5 | Proposed model | 95.1 | 94.4 | |

Conclusion

Medical data processing methods are efficient. Conventional echocardiography methodologies can simulate cardiograms, enhancing depictions of the organism's functioning. These methodologies can also evaluate alterations in cardiograms, reflecting biological processes. These simulations display the features of recorded changes and spectral parameters of cardiac impulses, including electric-potential conversion maps. This finding supports the initial hypothesis, the precision of the calculations and the importance of the operating procedure for interpreting the simulation parameters.

A simulation of the heart muscle, based on its static characteristics and shown as a sequence of pulses that vary over time and space, improves the effectiveness of diagnostic procedures by electronic cardiac systems.

The method of detailing diagnostic results displays the relationship between electrical and biometric processes in the heart muscle. This is necessary for cardiographic analysis, which develops novel methods for processing medical data obtained with electronic diagnostic systems. The incorporation of electrical, biometric and dynamic parameters into a simulation of the studied organism reduces errors in traditional methods of researching cardiac activity.

The employment of calculation techniques for electrophysiological signals, as outlined by the model, holds the potential to streamline diagnostic procedures, even in instances where undetected pathologies are present. The method is simple and can be applied to the development of various algorithms. Such a decision may be quite economically feasible.

One potential way to develop the proposed model is to integrate artificial intelligence, as it already has wide applications in various fields of medicine. Many studies show that the use of artificial intelligence in ECG interpretation has improved the accuracy and time required to diagnose various cardiovascular diseases.

Acknowledgement

The authors would like to thank Professor Vladimir Kuklin for discussions of this article and useful ideas.

Funding Information

The findings of this study were obtained under a 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 centres performing R&D on scientific and technological development priorities dated April 20, 2022, No. 075-15-2022-307.

Author's Contributions

Tagirbek Gaidarbekovich Aslanov: Conceptualization, investigation, original draft preparation, review and editing.

Naur Zamirovich Ivanov: Software, formal analysis, investigation, original draft preparation, review and editing, visualization.

Shamil Shamil'evich Anudinov: Validation, formal analysis, resources, original draft preparation, review and editing.

Tatiana Vladimirovna Karlova: Methodology, validation, data curation, original draft preparation, review and editing, supervision, project administration, funding acquisition.

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 that no ethical issues are involved.

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