Calculation Method for a Computer's Diagnostics of Cardiovascular Diseases Based on Canonical Decompositions of Random Sequences

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Abstract. The canonical decomposition of sequence describing the change of cardiograms is put in the basis of the method for a computer system of disease diagnostics. Obtained criterion of the solution of the problem of electrocardiograms classification is considerably simpler than the known criterion of making decision on the basis of the criterion of the maximum of density of distribution. The transition from multi-dimension density distribution to producing of uni-dimensional densities that allows to use random number of parameters of electrocardiograms for diagnostics is offered to carry out. The results of numerical experiment confirm the effectiveness of the offered method and high reliability of the processes of identification of cardiovascular diseases identification on the basis of its usage.

Keywords: calculation method, medical diagnostics, electrocardiogram, random sequence, canonical decomposition.

Key Terms: computation, mathematical model.

1 Introduction

At present, cardiovascular diseases head the list among the most widespread and dangerous diseases of modernity [1]. According to the data of the world Health Organization the death rate because of heart diseases in Ukraine reaches 64%, in the USA heart disease affects more than 800 000 people annually. At present the number of heart diseases among capable of working population sharply increased (quite often the age of the sick person with cardiac infarction doesn't exceed 23-25 years).

As heart diseases belong to the diseases which course and results of treatment directly depend on timely detection and elimination of pathological deviations the reliable diagnostics is the most important and primary task in the problem of cardiovascular diseases. As of today a great number of approaches [2-12] for the solving of the given task with the usage of different mathematical methods including statistical methods, methods of computational intelligence, fuzzy logic, neural network modeling algorithms and others are worked out.

Let us consider some related works concerning the methods for analysis of electrocardiograms using automated techniques, modern information technologies and computer systems. For example, such investigations were started at the University of Glasgow (Uni-G), United Kingdom more than 40 years ago and are continuing as Uni-G ECG Analysis Program [13] based on development of different approaches, in particular: methods for processing waveforms recorded in groups of three leads simultaneously, 12-lead ECG analysis program, optional approaches to computing the average QRS cycle including a simple mean, a weighted mean and a median beat, rhythm analysis, Brugada pattern, neural networks, rule based criteria, software diagnostic criteria based on age, sex, race, clinical classification, drug therapy and so on.

A dynamic hybrid architecture is descripted in [14] for ECG data analysis, combining the fuzzy with the connectionist approach. The data abstraction is performed by a layer of Radial Basis Function (RBF) units and the upcoming classification is carried out by a classical two-layer feedforward neural network. For the evaluation a large clinically validated ECG database is explored, but a more detailed description of the input space using a larger number of RBF units does not grant sufficient improvements.

Leiden ECG Analysis and Decomposition Software (LEADS) was developed [15] at the Leiden University Medical Center, The Netherlands as a MATLAB program for research oriented ECG/VCG analysis. LEADS focuses on the determination of a low-noise representative averaged beat (QRST complex), in which multiple parameters can be measured, paying special attention to the T wave. LEADS generates a default selection of beats for subsequent averaging.

The paper [16] presents the current status of principal component analysis (PCA) for ECG signal processing and describes the relationship between PCA and Karhunen-Loeve transform.

Several ECG applications based on PCA techniques have been successfully employed, including data compression, ST-T segment analysis for the detection of myocardial ischemia and abnormalities in ventricular repolarization, extraction of atrial fibrillatory waves for detailed characterization of atrial fibrillation, and analysis of body surface potential maps.

Advances in sensor technology, personal mobile devices, wireless broadband communications, and Cloud computing are enabling real-time collection and dissemination of personal health data to patients and health-care professionals anytime. This approach was proposed in [17] for creating an autonomic cloud environment for hosting ECG data analysis services.

A solution in [18] leverages the advance in multi-processor system-on-chip architectures, and is centered on the parallelization of the ECG computation kernel.

The article [19] reviewed time domain, frequency domain, premature complexes detection, heart rate variability, and nonlinear ECG analysis based methods.

Several different approaches for ECG analysis are based on a chaos theory [20], a combination of statistical, geometric, and nonlinear heart rate variability features [21], a semantic web ontology and heart failure expert system [22], learning system based on support vector machines [23], signal averaging method, multivariate analysis [24], RPCA - recursive principal component analysis [25], nonlinear PCA neural networks [26], cluster analysis, SPSA - simultaneous perturbation stochastic approximation method [27], ABT - Amplitude Based Technique, FDBT - First Derivative Based Technique, SDBT - Second Derivative Based Technique [28], Hilbert transform [29] and so on.

At the same time each from above-mentioned methods has its disadvantages and limitations. Just therefore the necessity of the working out of new effective methods of medical diagnostics didn't lose its actuality.

2 Statement of the problem

One of the most widespread methods of diagnostics and detection of cardiovascular diseases is an electrocardiography, a method of graphic registration of the characteristics of the electric field of a heart and their changes in the process of heart contractions. Electrocardiogram is characterized with a set of teeth by time and amplitude parameters of which the diagnosis is done. Taking into account that changing of the parameters of electrocardiogram has accidental character the problem of the classification of the realization of random sequence (some disease or absence of a disease correspond to every class) is the mathematical content of heart diseases diagnostics. For the purpose of the increase of the reliability of the diagnostics of cardiovascular diseases it is necessary to work out on the basis of the theory of random sequences the method of electrocardiogram recognition with taking complete account of their stochastic qualities.

3 Solution

The object of investigation is the random consequence $\{X\} = \{X(1), X(2), ..., X(12)\}$ with twelve elements each of which corresponds to some the most informative parameter of the electrocardiogram Fig. 1 (as appropriate the number of parameters can be increased): $X(1)$ is the width of the tooth P; $X(2)$ is the height of the tooth P; $X(3)$ is the interval P–Q; $X(4)$ is the height of the tooth Q; $X(5)$ is the interval QRS; $X(6)$ is the height of the first tooth R; $X(7)$ is the height of the second tooth R; $X(8)$ is the height of the tooth S; $X(9)$ is the interval Q-T; $X(10)$ is the height of the tooth T; $X(11)$ is the duration of the first cycle of the cardiogram; $X(12)$ is the duration of the second cycle of the cardiogram.

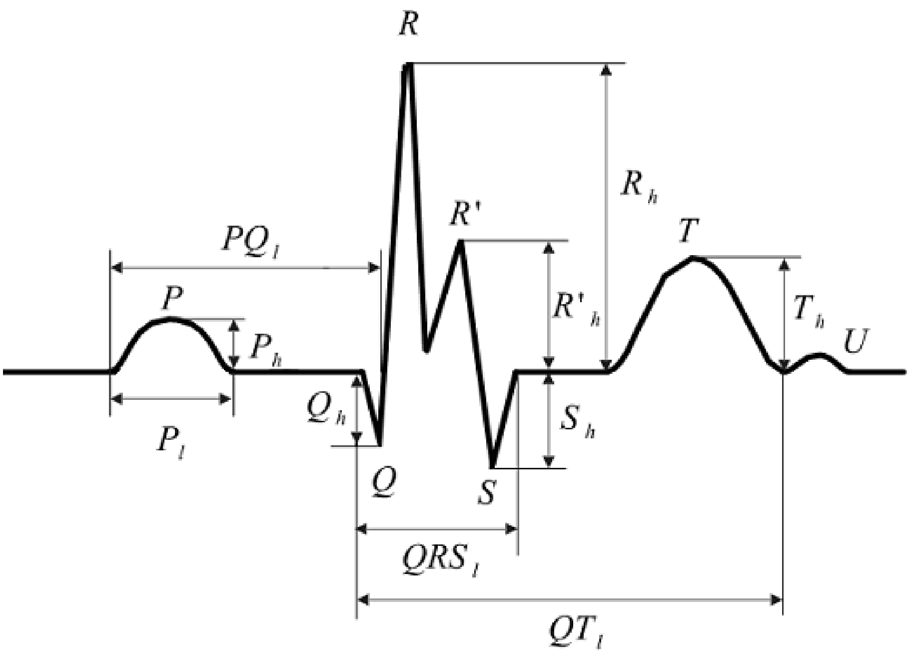

Fig. 1. Teeth and intervals on the cardiogram

As the result of electrocardiography conducting some sequence of values $x(i),\ i=\overline{1,12}$ about which it is known a priori that it is generated by one of the random sequences $X^{(j)}(i),\ i=\overline{1,12},\ j=\overline{1,J}$ ($J-1$ of diseases and normal state) is obtained. It is necessary to define to which of these sequences exactly (to which of J classes) relates to given realization. Formulated in such a way the problem of recognition completely comes to standard Bayes approach but during the usage of Bayes criterion improbable (and that is why especially dangerous) diseases can not be recognized. Thereupon for solving of the problem of medical diagnostics the most acceptable is the criterion of the maximum of probability according to which during the observation of the realization $\vec{x}=\{x(1),x(2),...,x(12)\}$ that hypothesis is taken which meets the condition:

$$j^{*}=\arg\max_{j}\left\{f_{12}\left(\vec{x}/j\right)\right\}, \tag{1}$$

where $f_{12}\left(\vec{x}/j\right),\ j=\overline{1,J}$ is the relative density distribution of the symptoms $\vec{x}$ provided that the realization belongs to the given class.

The problem of the recognition of random sequence realization comes to the determination of the belonging of the realization $\vec{x}$ to one of J given distributions $f_{12}\left(\vec{x}/j\right),\ j=\overline{1,J}$.

Thus the following stage is the assessment of the unknown densities $f_{12}(\vec{x}/j),\ j=\overline{1,J}$ that in its turn taking into account the great number of the results of $x(i),\ i=\overline{1,12}$ observations is quite difficult and laborious procedure. Given problem in the context of linear relations is essentially simplified [30] during the transition from sequence $x(i),\ i=\overline{1,12}$ to the analysis of the set of uncorrelated values $v_i,\ i=\overline{1,I}$, which are determined from the canonical model of random sequence [31] presentation:

$$X(i)=\sum_{\nu=1}^{i}V_\nu\varphi_\nu(i),\ i=\overline{1,12}, \tag{2}$$

$$V_i=X(i)-\sum_{\nu=1}^{i-1}V_\nu\varphi_\nu(i),\ i=\overline{1,12}, \tag{3}$$

$$\varphi_\nu(i)=\frac{1}{D_\nu}\left\{M\left[X(\nu)X(i)\right]-\sum_{j=1}^{\nu-1}D_j\varphi_j(\nu)\varphi_j(i)\right\},\ \nu=\overline{1,I},\ i=\overline{\nu,I}. \tag{4}$$

$$D_i=M\left[X^2(i)\right]-\sum_{\nu=1}^{i-1}D_\nu\varphi_\nu^2(i),\ i=\overline{1,12}\ , \tag{5}$$

where $\varphi_\nu(i),\ \nu,i=\overline{1,I}$ is nonrandom coordinate function: $\varphi_\nu(\nu)=1,\ \varphi_\nu(i)=0$, if $\nu>i$.

In this case the substitution of $\vec{x}$ for vector $\vec{v}$ taking into account $f_I(\vec{v}/j)=\prod_{i=1}^{12}f_1(v_i/j),\ j=\overline{1,J}$ allows to put down the criterion of decision making in the following form:

$$j^*=\arg\max_j\left\{\prod_{i=1}^{12}f_1(v_i/j),\ j=\overline{1,J}\right\}. \tag{6}$$

The problem of recognition thus comes to consecutive approximation of twelve one-dimensional densities of distribution. The stochastic algorithm of diagnostics becomes simpler essentially but the transition from the vector $\vec{x}$ to the vector $\vec{v}$ is possible provided that the random sequences $\{X(i)/j\},\ i=\overline{1,12},\ j=\overline{1,J}$ have only linear relations. Taking down of the limitations of the random sequences $X^{(j)}(i),\ i=\overline{1,12},\ j=\overline{1,J}$ normal distribution is possible as a result of the usage of the corresponding nonlinear canonical decomposition [32-35]:

$$V_i^{(\lambda)}=X^\lambda(i)-\sum_{\nu=1}^{i-1}\sum_{j=1}^{N}V_\nu^{(j)}\beta_{\lambda\nu}^{(j)}(i)-\sum_{j=1}^{\lambda-1}V_i^{(j)}\beta_{\lambda i}^{(j)}(i),\ i=\overline{1,12}; \tag{7}$$

$$D_\lambda(i)=M\left[X^{2\lambda}(i)\right]-\sum_{\mu=1}^{i-1}\sum_{j=1}^{N}D_j(\mu)\left\{\beta_{\lambda\mu}^{(j)}(i)\right\}^2-\sum_{j=1}^{\lambda-1}D_j(i)\left\{\beta_{\lambda i}^{(j)}(i)\right\}^2,\ i=\overline{1,12}; \quad (8)$$

$$\beta_{h\nu}^{(\lambda)}(i)=\frac{1}{D_\lambda(\nu)}\left(M\left[X^\lambda(\nu)X^h(i)\right]-\sum_{\mu=1}^{\nu-1}\sum_{j=1}^{N}D_j(\mu)\beta_{\lambda\mu}^{(j)}(\nu)\beta_{h\mu}^{(j)}(i)-\right.$$
$$\left.-\sum_{j=1}^{\lambda-1}D_j(\nu)\beta_{\lambda\nu}^{(j)}(\nu)\beta_{h\nu}^{(j)}(i)\right),\ \lambda=\overline{1,N},\nu=\overline{1,i}. \quad (9)$$

Taking into account different qualities of random sequences $\{X(i)/j\},\ i=\overline{1,12}, j=\overline{1,J}$ parameters of the canonical decomposition (7)-(9) are unique for each of the investigated sequences. The advantage of the decomposition (7)-(9) usage is that their independence follows from noncorrelatedness $V_i^{(N)},\ i=\overline{1,I}$ as all stochastic relations of much lower order are removed from the given coefficients. Thus the same as in the previous case the conversion of the problem of recognition from twelve measured space of the characteristics $\{X(1),...,X(12)\}$ into the space of the characteristics $\left\{V_1^{(N)},...,V_{12}^{(N)}\right\}$ of the same dimension simplifies the procedure of the assessment of the densities of distribution $f_{12}\left(v_1^{(N)},...,v_I^{(N)}/j\right)=\prod_{i=1}^{12}f_1\left(v_i^{(N)}/j\right),\ j=\overline{1,J}$ that comes to the approximation of twelve unidimensional densities of distribution. The criterion of making decision takes the following form

$$j^*=\arg\max_j\left\{\prod_{i=1}^{12}f_1\left(v_i^{(N)}/j\right),j=\overline{1,J}\right\}. \quad (10)$$

The absence of the assumptions about the kind of the density distribution of the random values $\left\{V_1^{(N)},...,V_{12}^{(N)}\right\}$ comes to the necessity of the usage of nonparametric methods for their description. The simplest and the most effective approach under given conditions is the usage of nonparametric assessments of Parzen-type [36]:

$$f_L\left(v_i^{(N)}\right)=\frac{1}{dL}\sum_{l=1}^{L}g(u_l), \quad (11)$$

where $u_l=d^{-1}\left(v_i^{(N)}-v_{i,l}^{(N)}\right),\ v_{i,l}^{(N)},\ l=\overline{1,L}$ are the realizations of the random value $V_i^{(N)},\ g(u_l)$ is a certain weigh function (kernel); d is a constant (coefficient of blurriness).

The choice in the capacity of the function of the kernel of $g(u)$ of steady density distribution allows to write down the expression for the assessment of the density distribution of $V_i^{(N)}$ in the following form:

$$f_L\left(v_i^{(N)}\right)=\frac{1}{dL}\sum_{l=1}^{L}g_l\left(v_i^{(N)}\right),$$

where

$$g_l\left(v_i^{(N)}\right)=\begin{cases}0{,}5, & v_{i,l}^{(N)}-d\le v_i^{(N)}\le v_{i,l}^{(N)}+d,\\ 0, & \left|v_i^{(N)}-v_{i,l}^{(N)}\right|>d,\end{cases}\quad l=\overline{1,L};$$

$$d=0{,}5\sup_l\left|v_{i,l}^{(N)}-v_{i,l-1}^{(N)}\right|,\ v_{i,l}^{(N)}>v_{i,l-1}^{(N)},\ l=\overline{2,L}.$$

The method of diagnostics of cardiovascular diseases on the basis of the offered algorithm and criterion of making decisions presupposes the fulfillment of the following phases:

Phase 1. Collection of statistic information about each investigated random sequence $X^{(j)}(i)$, i=$\overline{1,I}$, j=$\overline{1,J}$;

Phase 2. Calculation on the basis of the accumulated realizations $x_l^{(j)}(i)$, $i=\overline{1,I}$; $l=\overline{1,L_j}$; $j=\overline{1,J}$ for the investigated sequences $X^{(j)}(i)$, i=$\overline{1,I}$, j=$\overline{1,J}$ discretized moment functions $M\left[X_l^{\lambda}(v)X_h^{\mu}(i)\right]$;

Phase 3. Forming for each sequence $X^{(j)}(i)$, i=$\overline{1,I}$, j=$\overline{1,J}$ the canonical decomposition (7);

Phase 4. Obtaining on the basis of statistic information the assessments of one-dimensional densities of the distribution of the random coefficients of the canonical decompositions of the random sequences $X^{(j)}(i)$, i=$\overline{1,I}$, j=$\overline{1,J}$;

Phase 5. Decomposition of the recognizable realization by canonical expressions; calculation of the values of one-dimensional densities of distribution of coefficients formed as a result of decompositions; determination of the belonging of the realization of a certain random sequence $X^{(j^*)}(i)$, i=$\overline{1,I}$ (diagnostics of a disease) with the help of a rule (10);

Phase 6. Entry of the recognized realization $x^{(j^*)}(i)$, i=$\overline{1,I}$ into the base of statistical data of the corresponding random sequence $X^{(j^*)}(i)$, i=$\overline{1,I}$.

The scheme of the functioning of the system of cardiovascular diseases diagnostics is represented in Fig. 2.

In modern medicine more than one hundred different cardiovascular diseases are classified [1]. Developed six-stage algorithm is tested on five the most widespread diagnoses: “healthy heart” – is a random sequence $\{X(i)/1\},\ i=\overline{1,12}$; “hypertrophy of myocardium” - $\{X(i)/2\},\ i=\overline{1,12}$; “severe arrhythmia” - $\{X(i)/3\},\ i=\overline{1,12}$; “stenocardia of the 2d functional class” - $\{X(i)/4\},\ i=\overline{1,12}$; “neurocirculatory dystonia of light degree” - $\{X(i)/5\},\ i=\overline{1,12}$. The check of the statistical hypothesis about the independence of random coefficients of the canonical decomposition (7) on the basis of the criterion χ^2 showed the validity of the hypothesis by $N=3$ for all three sequences with the probability not less than $P_D=0{,}98$. Thus the decomposition (7) with the corresponding set of coordinate functions $\beta_{h\nu}^{(\lambda)}(i),\ h,\lambda=\overline{1,3},\ \nu,i=\overline{1,12}$ modifies into the adequate model of the investigated random sequence $\{X(i)/j\},\ i=\overline{1,12},\ j=\overline{1,3}$. For example, in Table 1 values $\beta_{1\nu}^{(1)}(i),\ \nu,i=\overline{1,12}$ for $\{X(i)/3\},\ i=\overline{1,12}$ are represented.

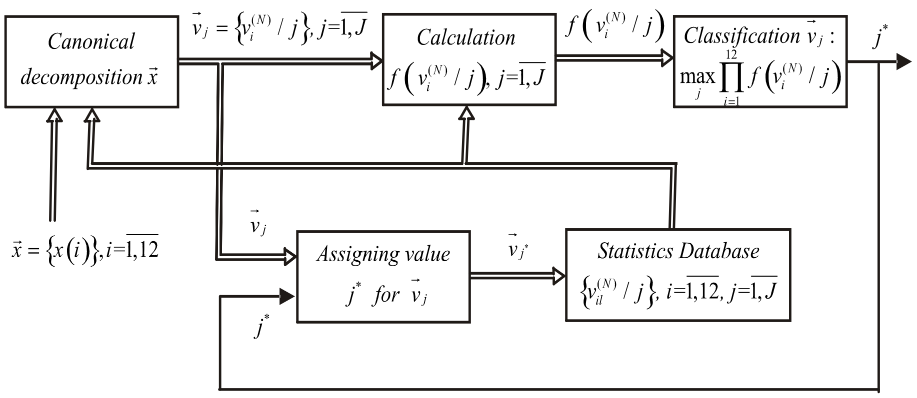

Fig. 2. Scheme of functioning of the computer system of cardiovascular diseases diagnostics

Recognition of the diagnoses was done on the basis of 200 different cardiograms for each disease. Comparative results of recognition of the diagnoses (a) on the basis of the developed by the authors calculating method, (b) on the basis of neuronic network [37] synthesized with the usage of Daubechies wavelet function of the 4th degree and Levenberg-Marquardt algorithm (for training) and (c) on the basis of the usage of fuzzy logic in medical diagnostics [3, 4] during the realization of the systems of fuzzy logic inference of Mamdani-type are presented in Table 2.

Neuronic network that was used in calculating experiment (Table 2) has the following pecularities.

1. Expressions for the determination of approximation coefficients and detailing of discrete wavelet transform are of the form [37]:

$$W_{\varphi}\left(j_0,k\right)=\frac{1}{M}\sum_{x} f\left(x\right)\varphi_{j_0,k}\left(x\right),$$

$$W_{\psi}\left(j,k\right)=\frac{1}{M}\sum_{x} f\left(x\right)\psi_{j,k}\left(x\right),$$

where $\varphi_{j,k}\left(x\right)$, $\psi_{j,k}\left(x\right)$ is a family of basic functions.

Table 1. Values of the coordinate function $\beta_{1\nu}^{(1)}\left(i\right)$ for random sequence $\left\{X\left(i\right)/3\right\}$, $i=\overline{1,12}$

	2	3	4	5	6	7	8	9	10	11	12
1	0,14	1,46	0,12	0,92	1,49	0,06	0,22	3,06	-0,36	7,11	5,66
2	1	6,50	0,34	3,81	5,70	0,37	1,56	12,5	-2,41	28,72	22,1
3	0	1	0,08	0,63	1,01	0,04	0,15	2,13	-0,24	4,91	3,92
4	0	0	1	4,22	9,07	0,72	1,12	14,1	-0,18	33,40	25,3
5	0	0	0	1	1,22	0,20	0,29	3,02	-0,25	6,42	5,46
6	0	0	0	0	1	0,08	0,15	1,61	-0,14	3,79	2,79
7	0	0	0	0	0	1	0,24	2,70	-0,53	6,16	5,05
8	0	0	0	0	0	0	1	5,69	-0,50	11,17	9,52
9	0	0	0	0	0	0	0	1	-0,07	2,12	1,82
10	0	0	0	0	0	0	0	0	1	-6,08	-4,1
11	0	0	0	0	0	0	0	0	0	1	0,83
12	0	0	0	0	0	0	0	0	0	0	1

2. Outcoming signal of each of separate neuron of outcoming layer was forming as

$$y\left(k\right)=\frac{1}{M}f\left(\sum_{i=0}^{K} w_{ki}\, f\left(\sum_{j=0}^{N} w_{ij}x\right)\right).$$

3. As activation function of each separate neuron continuous sigmoid bipolar function $f\left(x\right)=th\left(x\right)$ was being used.

In calculating experiment of the diagnostics of cardiovascular diseases on the basis of the realization of the mechanism of fuzzy logic inference [3,4] the following input parameters were used: x_1 - age of the sick; x_2 - double product of pulse on arterial tension; x_3 - tolerance to physical activity; x_4 - increase of double product per one kilogram of the body weight of the sick; x_5 - increase of double product per one kilogram of physical exertion; x_6 - adenosinetriphosphoric acid; x_7 - adenosine diphosphoric acid; x_8 - adenylic acid; x_9 - coefficient of phosphorilation; x_{10} - maximal consumption of oxygen per one kilogram of the body weight of the sick; x_{11} - increase of double product in the response for submaximal physical exertion; x_{12} - coefficient of the ratio of lactic and pyruvic acid content.

Expressions for the determination of the diagnosis are of the form:

$$d = f_d(x_1, y, z),$$

$$y = f_y(x_2, x_3, x_4, x_5, x_{10}, x_{11}),$$

$$z = f_y(x_6, x_7, x_8, x_9, x_{12}),$$

where values d (diagnosis), y, z are determined with the help of the knowledge base mentioned in the works of professor A. P. Rotstein [3,4].

Table 2. Results of the diagnostics of cardiovascular diseases (% of correct solutions)

	Healthy heart	Hypertrophy of myocardium	Severe arrhythmia	Stenocardia of the 2d functional class	Neurocirculatory dystonia of light degree
Method on the basis of canonical expansion	100%	100%	100%	98%	97%
Method on the basis of neural network	89%	92%	94%	86%	83%
Method on the basis of fuzzy logic	91%	90%	93%	91%	89%

The results of numerical experiment confirm high effectiveness of the developed calculating method in the comparison to the methods of artificial intelligence at the expense of the usage of optimal parameters during the formation of the criterion of making decision.

The choice of Daubechies function of the 4th degree from the existing limited set of wavelet functions in the capacity of the parameter of neural network is not optimal for solving of the problem of cardiovascular diseases diagnostics (usage of other functions leads to the worsening of quality of problem solution [37]).

The results of the experiment on the basis of A. P. Rotstein's approach [3, 4] indicate that the absence of strict mathematical apparatus of fuzzy equation analysis doesn't allow to form optimal structure of fuzzy rules that naturally restricts the accuracy of cardiovascular diseases classification.

On the whole the basis of statistic data can be expanded by the way of the introduction of cardiogram information about wider class or about all existing types of cardiovascular diseases. This will allow to form on the basis of developed calculating method highly efficient information systems of cardiovascular diseases diagnostics for their actual usage in medical cardiologic centers, clinics and diagnostic establishments.

4 Conclusions

Therefore in the work the calculation method for a computer system of cardiovascular diseases diagnostics on the basis of the canonical decomposition of the random sequence of electrocardiogram change is offered. The use of the mechanism of canonical decompositions allowed to formulate the decisive rule of the maximum of the combined density distribution in the form of the production of one-dimensional densities of distribution that gives the possibility to use for diagnostics random quantity of electrocardiogram parameters. Besides canonical decomposition doesn't impose any essential limitations (linearity, stationarity, Markovian property etc.) on the class of investigated random sequences. Thereby the offered approach to the solution of the problem of cardiovascular diseases diagnostics allows to take into account the maximum stochastic characteristics of the electrocardiograms belonging to different cardiovascular diseases. The given results of modeling show the high reliability of cardiovascular diseases diagnostics on the basis of the offered method.

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