Cardiovascular diseases diagnosis on the basis of neural network analysis of the biomedical signals

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Abstract

According to the World Health Organization, cardiovascular diseases (CVS) are one of the leading causes of death worldwide. People suffering from or at high risk of such diseases need constant supervision, early diagnosis and timely assistance.

Modern diagnostic systems are a compromise in the implementation of algorithms that require significant computational costs to achieve a medically acceptable accuracy and speed of diagnostics, and limited capabilities of computer hardware nodes. Methods of data mining, which allow to study complex nonlinear electrocardiosignals in the problem of diagnosing cardiac arrhythmias more fully, are considered in this paper.

The research goal is to improve the intelligent systems of arrhythmia diagnostics on the basis of neural network classifiers by developing a solution explaining subsystem based on neuro-fuzzy models.

Keywords: data mining, neural networks, fuzzy logic, electrocardiosignal, arrhythmia, digital signal processing.

1. Introduction

Cardiac arrhythmia as the most common disease is an irregular heart rhythm caused by improper operation of electrical impulses that regulate the heartbeat [1,2].

Cardiac arrhythmias can be classified according to the degree of danger to the patient. Figure 1 contains an arrhythmia types, divided into four groups. In each group, violations are arranged in ascending order of their influence on hemodynamics [3,4].

Arrhythmia can be detected by cardiac specialist using electrocardiogram (ECG) strip. Even for skillful cardiologist it may take several minutes to make a diagnosis; in some severe cases, this could be fatal for the patient. ECG analysis is too hard for the beginner or inexperience staff [3,4].

The electrocardiosignal (ECS) is an electrical manifestation of the heart contractile activity and it characterizes the state of the cardiovascular system (CVS). The recording of ECS is an electrocardiogram (ECG), the analysis of which is the most frequently used diagnostic test in CVS diseases intelligence.

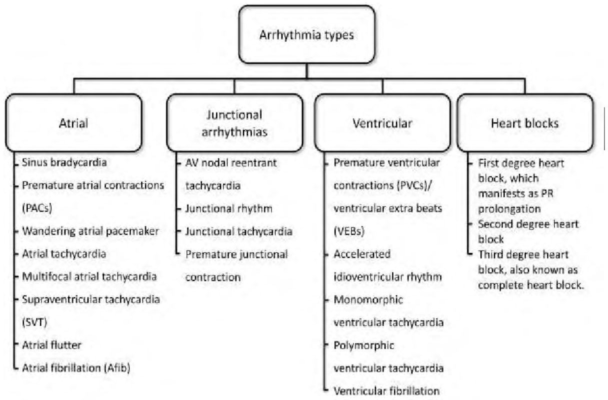

Fig. 1. Classification of the arrhythmia types

Electrocardiosignal on the ECG looks like a set of alternating waves, flat intervals and segments located on the baseline. Each element contains information of the state of the heart and its components [2]. ECS pattern is shown in the figure 1.

Typically, an ECG varies from person to person due to the difference in the position, size, anatomy of the heart, age, body weight, chest configuration, and other various factors. To improve the quality of diagnostics the analysis of ECG pattern and heart rate variability signal may have to be carried out over several hours. While making a diagnosis, medical expert takes into account the following features before making a decision: the relative positions of the waves, magnitudes, shapes, and other derived interval features such as PR interval, PR segment, and width of QRS, QT interval and ST segment [5]. Thus, the volume of the collected data is enormous and the ECG analysis is tedious and time consuming.

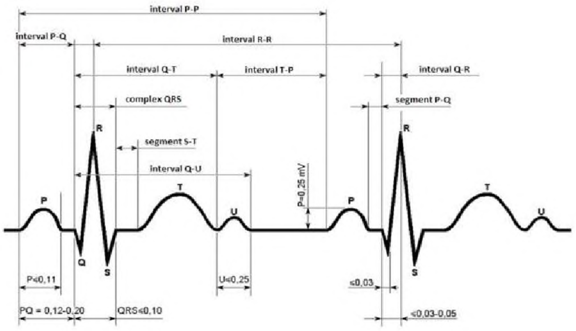

Fig. 1. Pattern of the electrocardiosignal

Therefore, the possibility of the analyst missing (or misreading) vital information increases [6].

2. Analysis of the nature of the electrocardiosignal as the main source of information for diagnosis of diseases

2.1. The problem of analyzing large amounts of ECG data

A typical cardiac computer aided diagnosis (CAD) system should handle various kinds of arrhythmias. Some arrhythmias appear irregularly. It is necessary recording ECG activity using, e.g., Holter monitor up to a week to successfully capture them [3]. The total number of such cardiac abnormalities reach up to 96 different categories [7]. Each of arrhythmia categories may contain nearly 28,800 beats, if 48 hours of single-channel ambulatory recording is considered, assuming an average heart-rate of about 60 beats-per-minute (BPM). The size of the database can be further increased if data is accumulated from multiple channels (up to 12).

2.2. Analysis of methods for the automatic diagnosis of cardiac arrhythmias

Figure 3 shows one of the possible classifications of methods currently used in automatic arrhythmia diagnosis systems [2-5,9,17,23,25,31]. General groups of methods are usually distinguished as linear, nonlinear and methods based on data mining (DM) [2, 10-13].

In [10] was discussed that linear methods in the problem of analysis of ECS do not allow to achieve an acceptable diagnostic accuracy, which is explained by the complexity of the signal and the nonlinear character of its changing. Non-linear methods of analysis require large computational costs and memory capacity for storing intermediate computational results.

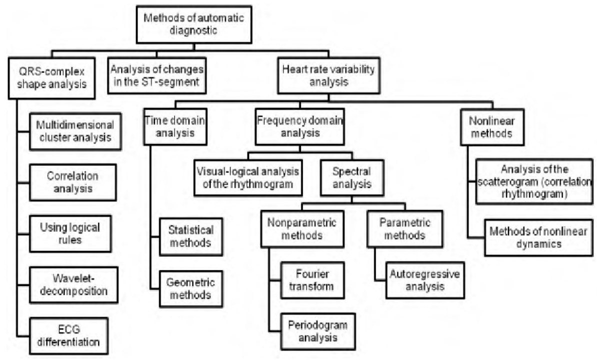

Fig. 3. Classification of methods of automatic arrhythmia diagnosis

The most important requirements are the high accuracy of the system, the operation on a device with low computational power in real-time (though training may be performed beforehand) and that diagnosis must not be related to the individual patient [8,9]. It is found out that the accuracy of arrhythmias detection in existing solutions does not exceed 80% [2,5,20].

2.3. The problem of constructing an automatic diagnostic system

The main difficulty in the task of automatic ECG analysis lies in the large scatter of the morphology of the ECG curves. Different patients have significantly changing parameters of the sequence of heartbeats (due to movements that produce high-frequency noises, or breathing, causing a baseline walk, or differences in the electrical characteristics of the body) [20]. The creation of a data set that would cover all possible ECG morphologies collected from different patients with various abnormalities in the functioning of the CVS is difficult. Therefore, diagnostic systems based on classifiers of different types, trained on the collected data, show unsatisfactory diagnostic results in the analysis of ECG samples of different patients [6,21,22] under real conditions of use.

2.4. Classification of medical system for monitoring and diagnosis of arrhythmias

The typical clinical decision support system should include

- ECG acquisition;
- pre-processing and noise removal which are baseline variation, electronic and electro-myographic noise etc, ECG delineation (P wave, QRS complex and T wave);
- feature extraction and beat classification.

Medical monitoring and diagnostic systems can be classified as:

- Stationary;
- Personal.

Basic data processing can be performed both:

- Autonomously;
- Remotely on the server.

The introduction and widening application of automatic external defibrillators (AEDs) make strong demands for ECS analysis. Highly accurate discrimination between shockable and non-shockable rhythms is required, with sensitivity and specificity aimed to achieve the maximum values [23]. Also, a false positive detection will initiate a defibrillator to give improper therapeutic intervention [24]. Development of new methods that will be both reliable in detection of anomalies in the patient's state and robust to noise and artifacts is difficult [25].

Various wearable devices will be the key components in the future for vital signs monitoring as they offer a non-invasive, remote and real-time medical monitoring means. Wireless Body Sensors (WBS) for cardiac monitoring are designed to early detect Cardio Vascular Diseases (CVD) by analyzing 24/24 and 7/7 collected ECS. Today, most of these WBS systems for CVD detection, include only limited automatic anomalies detection, particularly regarding ECG anomalies [26]. The reason for this is the limited performance of the microcontrollers used, which does not allow the use of modern algorithms for real-time analysis.

One the most important requirements are that the system have high accuracy, that it can operate on a device with low computational power in real-time (though training may be performed off-line) and that diagnoses are not tied to the individual patient [8].

In connection with the rapid development of mobile health technologies, personal medical monitoring systems (Holter monitors) are of special interest, which are mainly used only for data collection and offline processing. A portable medical device using a personal network (PAN) or the Body Area Network (BAN) can be integrated into the user's clothing.

Grand View Research estimated the volume of the mobile healthcare market (m-Health) for 2014 at $ 4.75 billion.

According to the Institute of Statistical Research and Knowledge Economy of the Higher School of Economics (HSE), by 2018 the total volume of this market can reach $ 26 billion – at an average annual growth rate of up to 61%.

By 2020 the proportion of wearable medical devices in the remote monitoring market will be 30% (37% will be only for smart watches). In 2017 the number of medical implantable and wearable devices will grow to 180 million units.

Modern diagnostic systems are a compromise between algorithms that require significant computational costs to achieve high accuracy of diagnostic, and hardware with limited performance.

It has been established that the accuracy of arrhythmia recognition in existing solutions does not often exceed 85% [2,10-13,17,25].

2.5. Data mining technologies in the problem of diagnosis of cardiac arrhythmias

The DM technologies are designed to search in large amounts of data of non-obvious, objective and useful regularities that reflect the objective internal data structure in comparison with the subjective opinion of the expert. The main purposes of the application of intelligent methods are:

- analysis of signals characterized by a high degree of uncertainty, e.g., "non-stochastic" type, which includes most biomedical signals, including ECS;
- increasing the level of intelligent assistance of medical specialists;
- revealing hidden regularities and extracting new knowledge from the accumulated data, which will allow to build production systems of explaining the diagnostic solutions.

To apply modern diagnostic methods to real ECS data, it is necessary to adapt existing methods of data mining, which allow to study complex nonlinear ECS more fully. CRISP-DM [27] (The Cross Industries Standard Process for Data Mining) is the most popular and widely used methodology. In accordance to the CRISP standard, data mining is a continuous process with many cycles and feedbacks.

Intelligent analysis of ECS data using neural network nonlinear models shows the highest results of recognition accuracy on model tasks [7,14-18]. Nevertheless, the distinctive feature of intelligent diagnostic systems based on the neural network technologies is the complexity of explaining the decision made. The reason is that signal processing algorithms and intermediate calculation results of neural network models are uninterpreted by both the medical technique and the knowledge engineer [2,19].

One of the possible solutions is the use of neuro-fuzzy models capable of realizing the functional of explaining a diagnostic solution on the basis of the construction of a system of production rules. The advantage of neuro-fuzzy models is the implementation of fuzzy inference in the neural network basis, which allows to adjust the parameters of models in the training mode [29].

The research goal is to improve the intelligent systems of arrhythmia diagnostics on the basis of neural network classifiers by developing a solution explaining subsystem based on neuro-fuzzy models.

To achieve the goal, the following tasks were set:

- Development of the structure of an intelligent system for diagnosing arrhythmias with a subsystem of explaining the solution based on neuro-fuzzy models;
- Development of a model of a subsystem of explaining the decision;
- Evaluation of the effectiveness of the proposed algorithms in the system of cardiac arrhythmias diagnostics.

3. Structure of an intelligent system of arrhythmia diagnosis

3.1. Generalized algorithm for detecting and identifying events based on the ECS analysis

Figure 4 shows a generalized algorithm for detecting and identifying events based on the ECS analysis. It begins with a preliminary assessment of the received signal and digital filtering procedure the task of which is noise suppression in the original signal. Then goes the QRS-complex selection and detection of its informative segments such as Q-, R-, S-, peaks of ventricular complex, the PQ and ST segments, and others, as well as measuring their parameters. Measurement is crucial to the signal analysis because the accuracy of the informative segments coordinates location and calculating their relative position determines the quality of further analysis of the cardiac activity and recognition of cardiac disorders. In subsequent phases it is produced an ECS analysis, including the calculation of the derivatives diagnostic features, analysis of amplitude and time attributes of the signal waveform. Process ends with the interpretation of the analysis results by classifying the processed signal to one of the classes of CVS conditions [2].

Figure 4 also provides the step of calculating the heart rate variability (HRV). HRV is the parameter of fluctuations in the value of intervals between successive contractions of the heart – R-R intervals. An additional measurement of this parameter is due to the fact that it can help improve significantly the accuracy of arrhythmias recognition, since there are uniform standards of measurement and interpretation of HRV in the analysis of sinus arrhythmia [30].

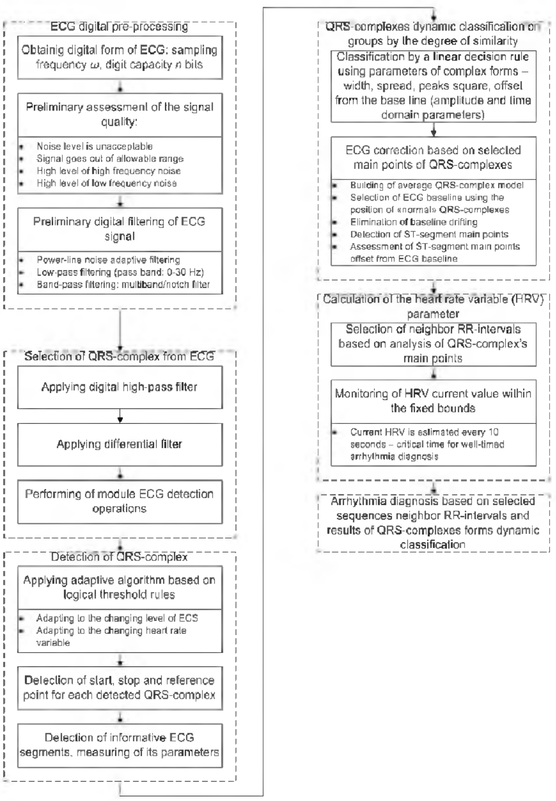

Fig. 4. Generalized ECG processing scheme

To analyze complex nonlinear ECS signals it is proposed to use the diagnosis methods based on DM methods and algorithms. Figure 5 shows a generalized scheme of the diagnostic model of detection and identification the events on the basis of the analysis of the ECS with the indicating of algorithms proposed for the implementation of each stage.

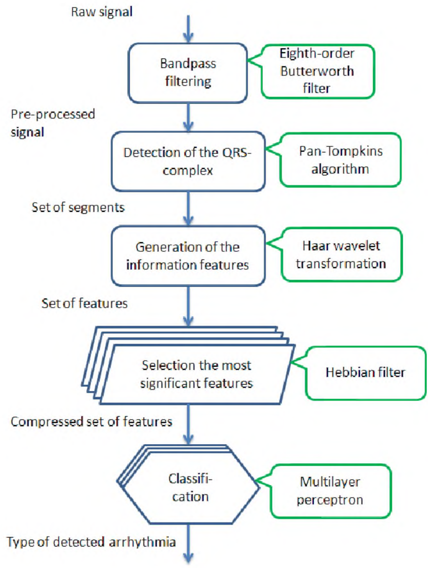

Fig. 5. Scheme of ECS analysis

The signal analysis for the diagnosis requires the identification of epochs (signal fragments associated with any studied event) and the research of relevant events. To detect the physiological events electrical activity of the heart it is proposed the use the Pan-Tompkins algorithm [2, 31].

This algorithm demonstrated a very low error value, which is about to 0.68%. Another advantage of the algorithm is that the waveform remains unchanged, while methods based on the signal differentiation change the shape substantially. Also event search is adaptive and does not depend on previously established parameters.

To generate diagnostic features, time localization of spectral components is needed as the ECS is a complex non-stationary periodic signal [2,17,18,23,24,34,35]. On this basis, to generate features it is proposed to use the result of the wavelet decomposition of the selected segment of the ECS, as it provides a time-frequency representation of the signal [17,24,34,35]. In the generation procedure Haar transformation is used repeatedly on the signal vector because of its computational simplicity and the possibility of full recovery of the original signal [33-35].

Next stage of signal processing is directed to compress the dimension of analyzed data without significant loss of useful information. The common method of solving this problem is the use of principal component analysis (PCA). However the disadvantage of this algorithm should be considered an intensive growth of computing costs while increasing the size of the original data [36]. Therefore, an alternative approach is proposed to implement the PCA using a single-layer neural network trained with the Hebbian rule. In this case each neuron acts as a filter selecting the appropriate principal component from the set of input data [36].

To stabilize the algorithm normalization of the weights is carried out to redistribute the balance between the synapses instead of unlimited growth. Training is subject to the set of synaptic weights, connecting the input layer nodes with the neurons.

Using Hebbian neural network do not require explicit constructing the covariance matrix and a large amount of hardware resources for storing matrix in the memory, as in the case of PCA [36].

The final stage of processing ESC is the classification of the QRS complexes on the type of disease using neural network classifier [5,6,21]. The most common architecture of the neural network to solve the problem of classification is multilayer perceptron (MLP) with one hidden layer [19,20,22].

The structure of the neural network, through which the last two stages of processing are implemented, allows us to organize calculations in a parallel form [24].

3.2. The structure of the subsystem for explaining the diagnostic solution adopted on the basis of a neuro-fuzzy network

The structure of the proposed intelligent diagnostic system combining neural network models and fuzzy logic models is shown in Figure 5.

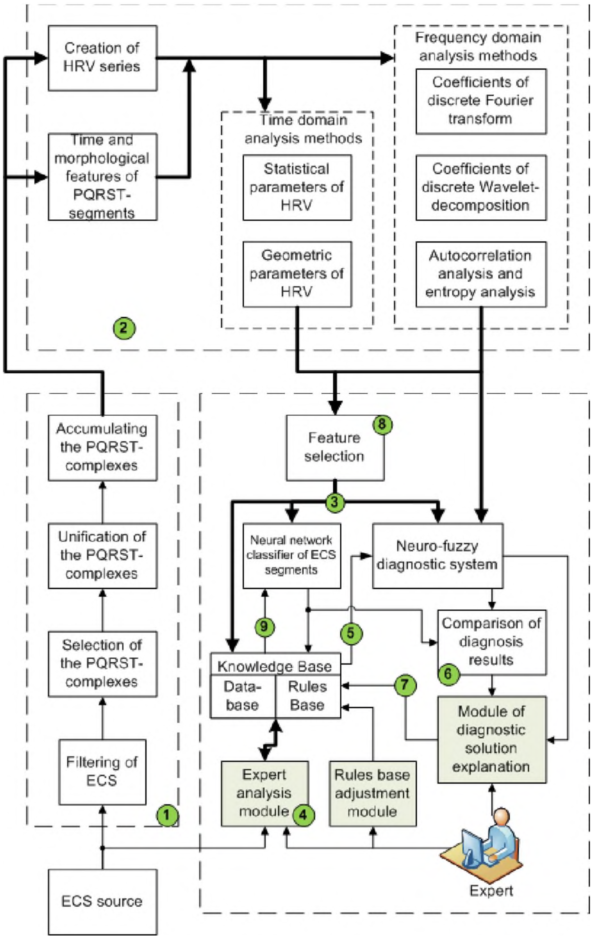

Fig. 5. Structure of the neuro-fuzzy diagnostic system

The system is divided into three blocks. The first block performs preprocessing of the raw ECS signal such as filtering the original signal and selecting the main segments describing the stages of cardiac contraction [13,18] – PQRST complex.

In block 2, the procedure of generating and pre-selecting features is implemented. Time-stamps – the duration of individual segments of the PQRST complex – are extracted from the signal and a time series of heart rate variability (HRV) is constructed, the analysis of which is widely used for the diagnosis of arrhythmias [37].

Character generation methods perform signal processing both in the time and frequency domains. Statistical methods of analysis compute the basic statistical parameters of a HRV series [37], while geometric methods are based on the analysis of the form of the distribution function of the HRV series [38].

Since changes in the heart rate are difficult to analyze in the time domain [37], spectral analysis methods [2, 39-41] are used to investigate the frequency properties of HRV and the marked initial ECS such as discrete Fourier transform, wavelet-decomposition of the signal, and also autocorrelation analysis [38].

3.3. Algorithm of functioning of the adopted diagnostic solution explaining subsystem

Nowadays, such structures as the Takagi-Sugeno-Kang model (TSK) or the Mamdani model are distinguished as classifiers based on a fuzzy inference with the possibility of adjusting the parameters of membership functions [12,15,28,30,32,37,38]. However, these models in the classical version use a full rule base, which limits their application for problems with a large number of input variables and terms. In this paper, it is proposed to use a structure based on the Mamdani model to classify the type of arrhythmias based on the fuzzy inference, adapting the parameters of the membership functions of the terms of input and output linguistic variables and constructing a base of fuzzy rules as a result of training based on self-organization.

The structure of the neuron used in the neural network interpretation of the fuzzy inference model is shown in Figure 6, the structure of the neuro-fuzzy model is shown in Figure 7:

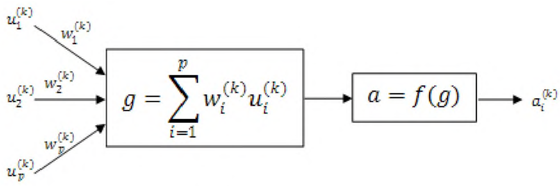

Fig. 6. Neuron structure

Notations of layers of the network are given in Table 1 for the description.

TABLE I. NOTATIONS OF LAYERS OF THE NETWORK

Notation	Description
k	– number of the layer
p	– amount of node's input links
$u_i^{(k)}$	– i-th input signal of k-th layer
$w_i^{(k)}$	– i-th link weigth k-th layer
g	– integration function
a	– neuron activation function
n	– amount of input variables
m	– amount of output variables
σ_{ij}, m_{ij}	– width and center of the Gauss activation function of j-th term of i-th linguistic variable
x_i	– input variable
y_i	– training sample
y'_i	– output variable
h_i	– amount of terms of i-th linguistic variable

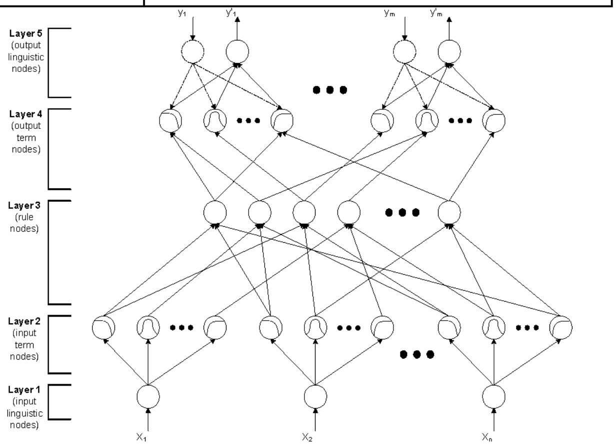

Fig. 7. Structure of the neuro-fuzzy module

The nodes in first layer transmit input values directly to the next layer:

$$u_i^{(1)} = x_i, g = u_i^{(1)}, a = g, w_i^{(1)} = 1, i = \overline{1,n}. \quad (1)$$

The second layer performs a fuzzification operation. The activation function of the neurons of this layer is a membership function of the corresponding term of the linguistic variable. In this case, the Gaussian function is selected as the activation function:

$$g = M_{x_i}^{j}(m_{ij}, \sigma_{ij})^2 = -\frac{\left(u_i^{(2)} - m_{ij}\right)^2}{\sigma_{ij}^2}, \quad (2)$$
$$a = e^g, j = \overline{1, h_i}.$$

The number of neurons of the third layer is equal to the number of fuzzy rules, defined as

$$numRules = \prod_{i=1}^{n} h_i. \quad (3)$$

At the outputs of this layer, the degree of activity of the rules is formed, which is defined as the minimum of the degrees of belonging calculated on the previous layer – the operation of the fuzzy “AND”:

$$g = \min_{i=\overline{1,p}} u_i^{(3)}, a = g, w_i^{(3)} = 1. \quad (4)$$

Neurons of the fourth layer operate in two modes: when transmitting a signal from the bottom to the top (operating mode) and when transmitting a signal from the top to the bottom (training mode). In the operating mode, neurons implement the composition of fuzzy subsets assigned to each output variable, using the sum of input signals with saturation – a fuzzy “OR” operation [29]:

$$g = \sum_{i=1}^{p} u_i^{(4)}, a = min(1, g), w_i^{(4)} = 1. \quad (5)$$

In the training mode, the neurons of this layer operate similarly to the neurons of the second layer.

As shown in the figure 7, the fifth layer consists of two types of neurons. In the training mode, a training sample is fed to the input of the first type of neurons , on the basis of which the parameters of the activation function of neurons of the fourth layer are tuned. Thus, neurons of this type (marked with dashed lines) operate similarly to the neurons of the first layer:

$$g = y_i, a = g. \quad (6)$$

In the operating mode, the second type of neurons of the fifth layer operates (marked by a solid line). Neurons of this type perform the defuzzification operation, for example, by the centroid method:

$$g = \sum w_{ij}^{(5)} u_i^{(5)}, a = \frac{f}{\sum \sigma_{ij} u_i^{(5)}}. \quad (7)$$

3.4. Neuro-fuzzy network learning algorithm

The learning algorithm [29,43] is divided into two phases:

1. Training on the basis of self-organization to initialize the membership functions of terms of input and output linguistic variables and the fuzzy rule base creation;
2. Supervised learning to adjust the parameters of the created membership functions and minimize the network error.

Figure 8 shows a block diagram of the algorithm for building and training the proposed system.

Phase 1. At the first stage expert manually determines the structure of the fuzzy system such as the number of terms of each input and output linguistic variable and the parameters of membership functions.

The second stage is responsible for the primary selection of membership functions and their parameters: center and width. It is proposed to use the method of competitive training [29,43]. It involves the independent iterative training of each neuron that implements the membership functions to the corresponding terms of linguistic variables. This training involves finding the minimum distance from the center of the membership function to the current input sample from the training sample.

To initialize the value of the width of membership functions, first nearest neighbor heuristic can be used, since in the second phase of learning the optimal values of the parameters will be determined.
At the third stage, fuzzy rules are formed. First, a complete rules base is created, which is a combination of all the conditions with all the conclusions (3).

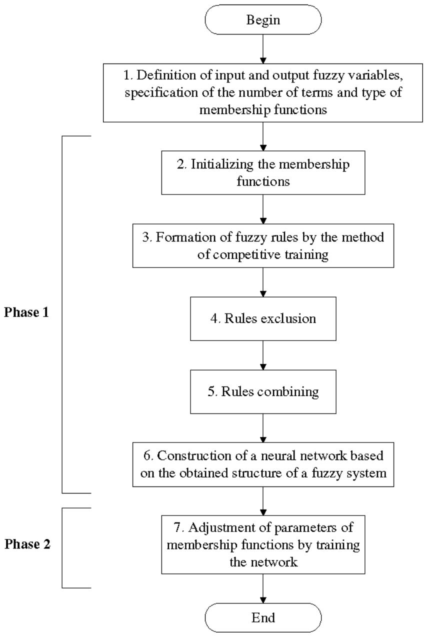

Fig. 8. Block diagram of the algorithm for building and training the neuro-fuzzy module

Then, the competitive learning algorithm is used to determine the required number of rules from the full database. Here the fourth layer neurons operate in the training mode and receive the training sample signals from the fifth layer. Denoting the output of the j-th neuron of the fourth layer as $o_j^{(4)}(t)$, and the production part of the i-th rule (the weighted sum of the signals entering the neurons of the 4th layer) as $o_i^{(3)}(t)$, calculate the links weights $\dot{w}_{ij}$ as:

$$\dot{w}_{ij}(t+1) = o_i^{(4)}(t) \cdot \left[w_{ij}(t) - o_i^{(3)}(t)\right]. \tag{8}$$

At the fourth stage, some rules are deleted. If there is more than one output connection for the neuron of the third layer, the connection with the largest weight is selected, and the remaining ones are deleted. It is also possible to delete all links and the neuron itself if the weights of all the links are less than a given threshold $\theta = 0.4$.

At the fifth stage, rules are combined to reduce their number. In Figure 7, the preconditional part of the rules is displayed by neurons of the third layer, and part of the consequent – by the connections of the fourth layer. To combine neurons of the third layer, it is proposed to use the following criteria:

1. Rules have exactly the same consequents;
2. Some preconditions are common to all the rule nodes in this set;
3. The union of other preconditions of these rule nodes composes the whole term set of some input linguistic variables.

   For example, the rules of the form:

$$\begin{aligned} &IF\ x_1 = A_1^{(1)}\ AND\ x_2 = A_1^{(2)}\ THEN\ y_1 = B_1, \\ &IF\ x_1 = A_1^{(1)}\ AND\ x_2 = A_2^{(2)}\ THEN\ y_1 = B_1, \\ &IF\ x_1 = A_1^{(1)}\ AND\ x_2 = A_3^{(2)}\ THEN\ y_1 = B_1 \end{aligned} \tag{9}$$

can be combined into one. If there is a group of neurons that meet these criteria, they can be replaced by one.

The sixth stage involves building a neural network with a complete structure and a set of elements and links. Then, optimization of activation function parameters values is done by supervised learning of the network. For example, a back propagation algorithm for can be used for training [19].

Phase 2. The task of finding the optimal values of the parameters of membership functions is formulated as follows: there is a set of input linguistic variables $x_i(t), i = 1, \dots, n$, the desired output values $y_i(t), i = 1, \dots, m$, and the base of fuzzy rules; it is required to find the optimal values of the membership function parameters, minimizing the error function

$$E = \frac{1}{2}\left(y(t) - \hat{y}(t)\right)^2, \tag{10}$$

where $\hat{y}(t)$ – actual output values.

The back propagation algorithm consists of forward and reverse signal passes through the layers of the network. A forward pass is needed to calculate the value $\hat{y}(t)$ at the current iteration and was considered above. On the reverse pass, the $\partial E/\partial y$ error is calculated for all hidden layers of the network. Assuming that w is a configurable node parameter, the generalized learning rule is expressed as

$$w(t+1) = w(t) + \eta \cdot \left(\frac{\partial E}{\partial w}\right), \tag{11}$$

where η – learning speed parameter.

Thus, the reverse pass, which calculates the error for the parameters of the center and the width of the Gaussian activation functions of layers 5 and 2, is determined by the expressions [29,43]:

Layer 5. Based on (8) and (4), it is obtained that

$$m_i(t+1) = m_i(t) + \eta[y(t) - \hat{y}(t)]\frac{\sigma_i u_i^{(5)}}{\sum \sigma_i u_i^{(5)}}. \tag{12}$$

$$\sigma_i(t+1) = \sigma_i(t) + \eta[y(t) - \hat{y}(t)] \cdot \frac{m_i u_i^{(5)}\left(\sum \sigma_i u_i^{(5)}\right) - \left(\sum m_i \sigma_i u_i^{(5)}\right) u_i^{(5)}}{\left(\sum \sigma_i u_i^{(5)}\right)^2}. \tag{13}$$

An error transmitted to the previous level is calculated as

$$\delta^{(5)} = -\frac{\partial E}{\partial a^{(5)}} = y(t) - \hat{y}(t). \tag{14}$$

Layer 4. Neurons of this layer are not subject to training, it is only needed to transmit the error signal to the previous layer:

$$\delta_i^{(4)}(t) = [y(t) - \hat{y}(t)] \cdot \tag{15}$$

$$\frac{m_i\sigma_i\left(\sum \sigma_i u_i^{(5)}\right) - \left(\sum m_i\sigma_i u_i^{(5)}\right)\sigma_i}{\left(\sum \sigma_i u_i^{(5)}\right)^2}.$$

Layer 3. Similarly with the layer 4, only the error value is calculated with (4) taking into account:

$$\delta_i^{(3)} = \delta_i^{(4)}. \qquad (16)$$

If the i-th neuron of layer 3 has more than one output, then the error signal will be equal to $\delta_i^{(3)} = \sum_k \delta_k^{(4)}$, where the summation is made over all outputs of the i-th neuron of the layer 3: error node, which is a rule, is the sum of the errors of the consequences (neuron outputs) of this rule.

Layer 2. The values of the parameter center of activation functions m_{ij} are defined as

$$m_{ij}(t+1) = m_{ij}(t) - \eta \frac{\partial E}{\partial a_i^{(2)}} e^{g_i} \frac{2(u_i^{(2)} - m_{ij})}{\sigma_{ij}^2}, \qquad (20)$$

and the width σ_{ij}, according to (2), (8), (11):

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) - \eta \frac{\partial E}{\partial a_i^{(2)}} e^{g_i} \frac{2(u_i^{(2)} - m_{ij})^2}{\sigma_{ij}^3}, \qquad (21)$$

where

$$\frac{\partial E}{\partial a_i^{(2)}} = \sum_k q_k, \qquad (22)$$

where the signals that include $a_i^{(2)}$are summarized and

$$q_k = \begin{cases} -\delta_k^{(3)}, a_i^{(2)}\ is\ min\ in\ k-th\ rule\ node's\ inputs \\ 0, otherwise \end{cases}. \qquad (23)$$

When using a neural network classifier, various parameters can be used as characteristics of the sample of the analyzed area of the ECS, related to the frequency, time, and parametric forms. The most common features used to create diagnostic systems are listed in the Table 2.

The key step in the analysis of the ECS in the diagnostic task is the construction of a classifier capable of deciding that the signal section belongs to a particular class of state in terms of the totality of the allocated features. When constructing the classifier, some or all of the characteristics listed in the table can be used. The source space of the characteristics can be transformed into one of the subspaces in which the separating hyperplane will have a simpler description. In this approach to the construction of an intelligent diagnostic system, it is difficult to implement a decision explanation subsystem.

With the use of a neuro-fuzzy classifier, it becomes possible to use the experience accumulated by cardiologists in the tasks of diagnosing certain types of arrhythmias. The existing medical methods can be adapted to a representation in a set of product rules of the form "IF-THEN", taking into account the adjustable weights that allow us to assess the degree of importance of both the individual feature and the rule as a whole.

Formalized expert knowledge in this case is transferred to the structure of the neuro-fuzzy module and becomes the core of the classifier. At the next stages of the diagnostic system construction, with DM techniques it becomes possible to identify hidden and unobvious patterns that complement expert knowledge, which will improve the accuracy of diagnosis. A feature of the use of neuro-fuzzy networks is the possibility of supervised learning on the existing base of marked samples assigned to different classes, which will allow to expand the base of diagnostic rules.

4. Experiment

Described procedure of ECS processing for arrhythmia recognition was implemented in MATLAB and tested on a sample from the database of arrhythmias "MIT-BIH Arrhythmia Database" [9]. From this base records of diseases of 5 classes were selected, total amount of records that have been classified is 29,537. The choice of these classes is due to a sufficient number of records required for a complete training of the classifier. Selected classes are given in the Table 2.

TABLE II. ARRHYTHMIA CLASSES DESCRIPTION

Class (type of arrhythmia)	Class code	Amount of records
Paced beat	C1	6977
Atrial premature beat	C2	2452
Left bundle branch block beat	C3	8018
Right bundle branch block beat	C4	7091
Normal beat	C5	4999

During the experiment on a sample from the database [9] it appears that nine principal components are enough to save 95% of the variance of the original signal. Thus, the Hebb filter comprises 9 neurons [36]. Figure 9 shows the contribution of each subsequent principal component to the total variance (histogram) and the total variance of all included principal components (line).

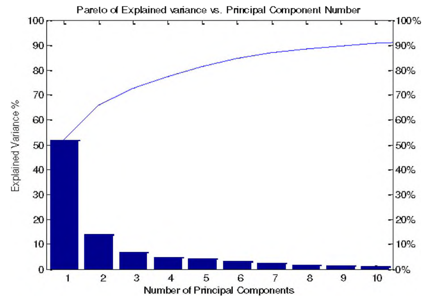

Fig. 9. Determining the required number of principal components

The structure of the multilayer perceptron, with the help of which the last two stages of processing are realized, allows to organize calculations in a parallel form [24]. In this research it was determined that 9-32-5 structure is sufficient to obtain a high precision classification.

Cross-validation was performed to analyze the generalization capability of the algorithm. Results obtained after ten passes of the algorithm are shown in Tables 8 and 9.

TABLE III. COMPUTATION RESULTS

Parameter	Value
Sensitivity	0.903
Specificity	0.970
Positive Predictive Value	0.904
Negative Predictive Value	0.969
Amount of records	29537

Correctly recognized	25565 (86,55%)
Prediction error	3972 (13,45%)

TABLE IV. CROSS-VALIDATION RESULTS

Predicted / Actual	C1	C2	C3	C4	C5
C1	(6299) 90,28%	(107) 1,53%	(466) 6,68%	(63) 0,9%	(42) 0,6%
C2	(132) 5,38%	(1138) 46,41%	(215) 8,77%	(38) 1,55%	(929) 37,89%
C3	(357) 4,45%	(119) 1,48%	(6911) 86,19%	(2) 0,02%	(629) 7,84 %
C4	(125) 2,5%	(1) 0,02%	(37) 0,74%	(4836) 96,74%	(0) 0%
C5	(57) 0,8%	(263) 3,71%	(389) 5,48%	(1) 0,01%	(6381) 89,99%
Unclassified	0	0	0	0	0

5. Results discussion

Table 9 should be read line by line: from all the records of class C1 90.28% were detected correctly, 1.53% of the records were recognized as a class C2, 6.68% – as a class C3, etc. The table shows that the total recognition errors within the class do not exceed 15% on average. The only exception was the class C2, about 38% of which records were wrongly attributed to the class C5. This is explained by the fact that the records number of class C2 is about 2.5 times less than that of the other classes.

The next step is the implementation of a subsystem for explaining the solution explaining subsystem based on neuro-fuzzy module.

For a preliminary estimate of the size of the rule base, let us determine the number of linguistic variables, as well as the type and number of terms for each variable. If the basic approach to constructing a complete system of rules in the Mamdani or TSK fuzzy inference model is used, then for the nine input linguistic variables and 5 fuzzy terms [29], the number of rules will be 1953152.

According to the stage 4 of the 1st phase of NFS training, after excluding the rules their number will decrease by 3 times and become equal to 651041. However, such a number of rules is too large for the subsequent application of the self-organization algorithm in the current implementation to reduce the number of rules. Therefore, a procedure that allows to form a certain number of rules on the basis of expert data, with the possibility of further expansion of the base and the refinement of the parameters of the fuzzy variable membership functions is needed. The possible formalization of the characteristics of certain types of arrhythmias presented above makes it possible to form the core of the production system from an essentially smaller number of rules.

6. Conclusions

In this paper an approach to improve the intelligent systems of arrhythmia diagnostics on the basis of neural network classifiers by developing a solution explaining subsystem based on neuro-fuzzy models is proposed.The analysis of modern methods of automatic diagnosis of cardiac arrhythmias is carried out. It is established that the correctness of diagnostics of the most common algorithms in automated diagnostic systems does not exceed 80%.

The structure of a diagnostic system for the detection of cardiac arrhythmias based on intellectual data mining technology is proposed.

The choice of algorithms for processing ECS at the respective stages of analysis is due to the possibility of their parallel implementation in order to improve the efficiency of diagnostics in real time by improving the accuracy of the recognition of arrhythmias of different classes.

Evaluation of the effectiveness of the proposed algorithms was performed on a sample from the arrhythmia database “MIT-BIH Arrhythmia Database”. As a result of analysis of 29 537 records of diseases of the 5th class, the correctness of arrhythmia recognition was about 86%. It is shown that using the neuro-fuzzy classifier it becomes possible to use the experience accumulated by cardiologists in the tasks of diagnosing certain types of arrhythmias. A model of the neuro-fuzzy solution explaining module is proposed to formalize the expert knowledge.

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