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(Eds.)

IDDM International Conference

Proceedings of the 3rd International Conference on Informatics & Data-Driven Medicine (IDDM 2020)

Växjö, Sweden
November, 2020

Shakhovska N., Campos J., Melnykova N., Izonin I., (Eds.): The 3rd International Conference on Informatics & Data-Driven Medicine (*IDDM 2020*), Växjö, Sweden, November 19-21, 2020, CEUR-WS.org, online

This volume represents the proceedings of the 3rd International Conference on Informatics & Data-Driven Medicine, held in Växjö, Sweden, in November, 2020. It comprises 50 contributed papers that were carefully peer-reviewed and selected from 102 sub-missions.

CEUR Workshop Proceedings
http://ceur-ws.org
ISSN 1613-0073

Vol-2753
urn:nbn:de:0074-2753-4

IDDM 2020
The 3rd International Conference on Informatics & Data-Driven Medicine

Proceedings of the 3rd International Conference on Informatics & Data-Driven Medicine

Växjö, Sweden, November 19 - 21, 2020.

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2020-11-25: submitted by Ivan Izonin, metadata incl. bibliographic data published under Creative Commons CC0
2020-12-01: published on CEUR Workshop Proceedings (CEUR-WS.org, ISSN 1613-0073) |valid HTML5|

Processing Methods and ECG Signal Recognition Model

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Abstract

In the work for processing the ECG signal, methods for determining the length of RR interval of ECG signal and calculating on its basis the boundaries of RR interval of ECG signal, geometric converting of RR intervals of ECG signal have been proposed. The proposed definition of the length of RR interval of ECG signal uses statistical estimation of local maximum and band-pass filtering, which decreases the computational complexity, and decreases the dependence on noise and permit to use dynamic threshold, which increases the accuracy of calculating the length and boundaries of RR intervals of ECG signal. The proposed geometric converting of RR intervals of ECG signal makes it possible to convert RR intervals to a unified amplitude-time window, which permits to form samples of ECG signal on basis its structure. The proposed model of ECG signal recognition is based on adaptive probabilistic neural network that allows identification of the structure and parameters, which increases the recognition probability. The proposed method for identifying the structure and parameters of the model for recognizing ECG signal samples is based on adaptive clustering, which provides a high degree of compression and clustering of ECG signal samples. To evaluate the proposed methods and model, quality criteria are determined. Numerical studies, which allow to evaluate the proposed methods and model, have been carried out. The proposed methods and model make it possible to formulate and solve the problems of structuring, transforming and recognizing the ECG signal, which is used for ECG diagnostics.

Keywords 1

ECG diagnostics, ECG signal structuring, calculation of length of RR interval, determination of boundaries of RR intervals, geometric transformation of RR intervals, adaptive probabilistic neural network, identification of structure and parameters of model for recognizing ECG signal patterns

1. Introduction

Automated medical diagnostics of a person means decision making based on the analysis of a digital signal, which increases the quality of diagnostics of the person under study. In contrast to the traditional approach, computer medical diagnostics accelerates and increases the accuracy of the identification process, which is critical in case of limited time.

A important class of medical diagnostics of a person is formed by methods based on the recognition of electrocardiograms (ECG) [[1], [2], [3], [4]].

To analyze the ECG signal, traditional speech recognition methods, such as:

- dynamic programming [[5], [6]];

IDDM'2020: 3rd International Conference on Informatics & Data-Driven Medicine, November 19–21, 2020, Växjö, Sweden
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- vector quantization [[7], [8]];
- artificial neural networks [[9], [10]];
- decision tree [[11], [12]];
- a combination of these methods [[13]],

can be used, which, when identifying a signal, split it into frames (have the same length) without analyzing its structure, which decrease the efficiency of ECG diagnostics.

The highest probability of ECG signal recognition is achieved by means of neural networks.

Currently, the following artificial neural networks are commonly used to recognize ECG signals:

- multilayer perceptron (MLP) [[14], [15]],
- neural network based on radial basis functions (RBFNN) [[16], [17]];
- probabilistic neural network (PNN) [[18], [19]]
- support vector machine (SVM) [[20], [21]];
- self-organizing feature map (SOM) [[22], [23]].

These artificial neural networks have next disadvantages:

- there is no automatic calculation of the number of hidden layers;
- there is no automatic calculation of the number of neurons in hidden layers;
- it is required to store all training patterns;
- possess a high computational complexity of learning;
- do not have a high recognition probability;
- methods of local search are used for training, which can lead to falling into a local extremum.

In this regard, it is relevant to choose a model and create a method for identifying its structure and parameters, which will eliminate the indicated disadvantages.

The structuring of ECG signal is based on the division of ECG signal based on the length of RR interval.

To determine the length of RR interval, traditional methods for calculation the fundamental tone of a person, such as [[24], [25]]:

- wavelet-spectral (amplitude-time-frequency) methods;
- amplitude-time methods;
- cepstral (maplitude-quefrency) methods;
- spectral (amplitude-frequency) methods;

These methods have next disadvantages:

- do not use dynamic threshold, which increases the accuracy of calculating the length of RR interval.
- possess a high computational complexity;
- depend on noise level, which decreases the accuracy of calculating the length of RR interval;

In this regard, it is relevant to develop a method for structuring the ECG signal, which will eliminate the indicated disadvantages.

As geometric transformations of ECG signal, scaling and shifting are usually used.

To scale a discrete ECG signal, a transition to a continuous one by interpolation with subsequent sampling of scaled ECG signal is usually used.

In this regard, it is relevant to create processing methods and ECG signal recognition model, which will eliminate the indicated disadvantages.

The goal of the article is to increase the efficiency of ECG diagnostics due to processing methods and ECG signal recognition model.

To reach this goal, it is necessary to solve the next tasks:

1. Creation of a method for structuring and transforming an ECG signal.
2. Determination of quality criterion of ECG signal structuring.
3. Selection of a model for recognizing ECG signal patterns.
4. Determination of quality criterion for recognizing ECG signal patterns.
5. Development of a method for identifying the structure and parameters of the model for recognizing ECG signal patterns.
6. Determination of characteristics and quality criterion of identification of the structure and parameters of the model for recognizing ECG signal patterns.

2. Method of structuring and transforming the ECG signal

Training sample formation method includes:
1. Calculation of the length of RR interval based on statistical estimation of local maximum and band-pass filtering.
2. Calculation of the boundaries of RR intervals based on the fundamental tone.
3. Geometric converting of RR intervals to a unified amplitude-time window.

2.1. Determination of the length of RR interval of ECG signal based on statistical estimation of local maximum and band-pass filtering

The article proposes a method for calculating the length of RR interval of ECG signal based on statistical estimation of local maximum and band-pass filtering, which includes the next steps:

1. Set ECG signal $y(h)$, $h \in \overline{1, H^f}$. Set the lower cutoff frequency in Hz $f1$, $f1 = 5$. Set filtering parameter α, $0 < \alpha < 1$. Set the upper cutoff frequency in Hz $f2$, $f2 = 35$. Set the number of windows in length H, $H = 2^b$, where the parameter *b* is selected from the condition $b - 1 < \log_2\left(f_d / f_{\min}\right) < b$, f_d is the sampling frequency of ECG signal in Hz, $f_{\min}$ is the minimum frequency of R wave in Hz (for $f_d = 360$, $f_{\min} = 5$), $[\cdot]$ is the integer part.
2. Divide ECG signal into windows:
$$s_i(h) = y((i-1) * H + h + 1),\ h \in \overline{0, H-1},\ i \in \overline{1, I}\ .$$
3. Preprocessing of windows using a low-pass filter:
$$\breve{s}_i(h) = s_i(h+1) - \alpha s_i(h),\ h \in \overline{0, H-1},\ i \in \overline{1, I}\ .$$
4. Determinate the spectrum of weighted windows using weighting with Hamming window and forward discrete Fourier transform:
$$\widehat{s}_i(h) = \breve{s}_i(h) w(h),\ h \in \overline{0, H-1},\ i \in \overline{1, I}\ ,$$
$$\widehat{S}_i(l) = \sum_{h=0}^{H-1} \widehat{s}_i(h) e^{-j(2\pi/H)lh},\quad l \in \overline{0, H-1},\ i \in \overline{1, I}\ ,$$
$$\tilde{S}_i(l) = \begin{cases} \widehat{S}_i(l), & \dfrac{f1 \cdot H}{f_d} \le l \le \dfrac{f2 \cdot H}{f}, \\ 0, & \dfrac{f1 \cdot H}{f_d} > l \vee l > \dfrac{f2 \cdot H}{f}, \end{cases},$$
$$l \in \overline{0, H-1},\ i \in \overline{1, I}\ ,$$
$$w(h) = 0.54 + 0.46 \cdot \cos\frac{2\pi h}{H},$$
where $w(h)$ is the Hamming window.
5. Compute the inverse discrete Fourier transform of filtered windows:
$$\tilde{s}_i(h) = \operatorname{Re}\left(\frac{1}{H} \sum_{h=0}^{H-1} \tilde{S}_i(l) e^{j(2\pi/H)lh}\right),\quad h \in \overline{0, H-1},\ i \in \overline{1, I}\ .$$
6. Combine filtered windows into ECG signal:
$$\tilde{y}((i-1) \cdot H + h + 1) = \tilde{s}_i(h),\ h \in \overline{0, H-1},\ i \in \overline{1, I}\ .$$
7. Determinate the positions of local maximum in the filtered R segment.
   7.1. Set the sample index $h = 1$. Set the count of local maximum $Q = 0$.
   7.2. If $\tilde{y}(h) > \tilde{y}(h-1) \wedge \tilde{y}(h) > \tilde{y}(h+1) \wedge \tilde{y}(h) > 0$, then fix the point of the local maximum, i.e. $e_{Q+1} = h$, increase the count of local maximum, i.e. $Q = Q + 1$.
   7.3. If $h < H^r - 1$, then go to the next sample, i.e. $h = h + 1$, go to step 7.2.

8. Determinate distances between local maximum in the filtered R segment

$$\Delta_n = e_{n+1} - e_n,\ n \in \overline{1, Q-1}.$$

9. Determinate mean of distances:

$$\mu = \frac{1}{Q-1}\sum_{n=1}^{Q-1}\Delta_n .$$

10. Determinate standard deviation of distances:

$$\sigma = \sqrt{\frac{1}{Q-1}\sum_{n=1}^{Q-1}(\Delta_n)^2 - \mu^2} .$$

11. Delete outliers from distances.
    11.1. Set the count of new distances $\tilde{Q} = 0$ .Set distance index $n = 1$.
    11.2. If $\mu - \sigma \le \Delta_n \le \mu + \sigma$, then fix a new distance ($\tilde{\Delta}_{\tilde{Q}+1} = \Delta_n$), increase the count of new distances ($\tilde{Q} = \tilde{Q} + 1$).
    11.3. If $n < Q-1$, then go to the following distance, i.e. $n = n+1$, go to step 11.2.
12. Determinate the length of RR interval as a mean of new distances:

$$N^{FT} = \frac{1}{\tilde{Q}}\sum_{n=1}^{\tilde{Q}}\tilde{\Delta}_n .$$

As a result, the length of RR interval is determined.

2.2. Determination of the boundaries of RR intervals of ECG signal

The author's method for calculating the boundaries of RR interval of ECG signal includes the following steps:

1. Set ECG signal $y(h)$, $h \in \overline{1, H^f}$. Set the parameter γ for determining the boundaries of RR intervals of ECG signal, $0 < \gamma < 1$. Set the length of RR interval of ECG signal.
2. Initialize the variables to determine the boundaries of RR intervals of ECG signal in the form:

$$H_0^{\max} = \arg\max_h y(h),\ h \in \{1,...,\gamma H_0^{FT}\},$$

$$H_0^{FT} = H^{FT} .$$

3. Set the count of RR interval of ECG signal $I = 1$.
4. Calculating the boundaries of RR interval of ECG signal in the form:

$$H_I^{\min} = H_{I-1}^{\max} ,$$

$$H_I^{\max} = \arg\max_h y(h),\ h \in \{H_I^{\min} + (1-\gamma)\cdot H_{I-1}^{FT},...,H_I^{\min} + (1+\gamma)\cdot H_{I-1}^{FT}\},$$

$$H_I^{FT} = H_I^{\max} - H_I^{\min} .$$

5. If $H_I^{\max} \le H^f$, then increase the count of quasiperiodic fluctuations, i.e. $I = I+1$, go to step 4.

Set of boundaries of quasiperiodic segment fluctuations are formed.

2.3. Geometric transformation of RR intervals of ECG signal to a unified amplitude-time window

The paper proposes a method of geometric transformation of RR intervals of ECG signal to a unified amplitude-time window, which consist the next steps:

1. Set ECG signal $y(h)$, $h \in \overline{1, H^f}$. Set the count of quantization levels of ECG signal L (for an 11-bit pattern $L = 2048$) and set of boundaries of RR intervals of ECG signal $\{(H_i^{\min}, H_i^{\max})\}$,

$i \in \overline{1, I}$, where I is the count of patterns. Set the length of the amplitude-time window H, $H = 2^b$, where the parameter b is selected from the condition $b-1 < \log_2 \left(f_d / f_{\min} \right) < b$, f_d is the sampling frequency of ECG signal in Hz, $f_{\min}$ is the minimum frequency of R wave in Hz (for $f_d = 360$, $f_{\min} = 5$).

2. Calculate the maximum and minimum values of the transformation of RR intervals of ECG signal in the form:

$$A_i^{\max} = \max_h y(h),\ h \in \{H_i^{\min}, ..., H_i^{\max}\},$$

$$A_i^{\min} = \min_h y(h),\ h \in \{H_i^{\min}, ..., H_i^{\max}\}.$$

3. Calculate a finite family of discrete patterns shifted in amplitude and time, defined by a finite set of integers bounded finite discrete functions $X^s = \{x_i^s \mid i \in \{1, ..., I\}\}$, in the form:

$$x_i^s(h) = \begin{cases} y(h + N_i^{\min} - 1) - A_i^{\min}, & h \in \{1, ..., H_i + 1\}, \\ 0, & h \notin \{1, ..., H_i + 1\}, \end{cases}$$

$$H_i = H_i^{\max} - H_i^{\min},$$

$$A_i = A_i^{\max} - A_i^{\min}.$$

4. Calculate a finite family of continuous patterns obtained as a result of interpolation and defined by a finite set of real-valued bounded finite continuous functions $\Psi = \{\psi_i \mid i \in \{1, ..., I\}\}$ in the form:

$$\psi_i(t) = \begin{cases} \sum_{h=1}^{H_i} \chi_{(t_h, t_{h+1})}(t) \left(x_i^s(h) + \frac{x_i^s(h+1) - x_i^s(h)}{\Delta t}(t - t_h) \right) + \sum_{h=1}^{H_i+1} \chi_{\{t_h\}}(t) x_i^s(h), & \forall t \in [\breve{T}^{\min}, \breve{T}^{\max}], \\ 0, \quad \forall t \notin [\breve{T}^{\min}, \breve{T}^{\max}], \end{cases}$$

$$\breve{T}^{\min} = \Delta t,\ \breve{T}^{\max} = 2^b \Delta t,\ t_n = h \Delta t,$$

$$\chi_B(t) = \begin{cases} 1, & t \in B, \\ 0, & t \notin B, \end{cases}$$

where Δt is the quantization step by time of ECG signal, $\chi_B(t)$ is the indicator function.

5. Calculate a finite family of time-scaled and time-shifted continuous patterns defined by a finite set of real-valued bounded finite continuous functions $\Psi^s = \{\psi_i^s \mid i \in \{1, ..., I\}\}$ in the form:

$$\psi_i^s(t) = \begin{cases} \psi_i \left(T_i \frac{t - \breve{T}^{\min}}{\breve{T}^{\max} - \breve{T}^{\min}} \right), & \forall t \in [\breve{T}^{\min}, \breve{T}^{\max}], \\ 0, & \forall t \notin [\breve{T}^{\min}, \breve{T}^{\max}], \end{cases}$$

$$\breve{T}^{\min} = \Delta t,\ \breve{T}^{\max} = 2^b \Delta t.$$

6. Calculate a finite family of amplitude-scaled and amplitude-shifted continuous patterns defined by a finite set of real-valued bounded finite continuous functions $\Psi^{ss} = \{\psi_i^{ss} \mid i \in \{1, ..., I\}\}$ in the form:

$$\psi_i^{ss}(t) = \begin{cases} \breve{A}^{\min} + \frac{\breve{A}^{\max} - \breve{A}^{\min}}{\tilde{A}_i^{\max} - \tilde{A}_i^{\min}} \psi_i^s(t), & \forall t \in [\breve{T}^{\min}, \breve{T}^{\max}], \\ 0, \ \forall t \notin [\breve{T}^{\min}, \breve{T}^{\max}], \end{cases}$$

$$\tilde{A}_i^{\max} = \max_t \psi_i^s(t),\ t \in [\breve{T}^{\min}, \breve{T}^{\max}],$$

$$\tilde{A}_i^{\min} = \min_t \psi_i^s(t),\ t \in [\breve{T}^{\min}, \breve{T}^{\max}],$$

$$\breve{A}^{\min} = 1,\ \breve{A}^{\max} = L.$$

7. Calculate a finite family of discrete patterns converted from continuous patterns by sampling in time and defined by a finite set of integer bounded finite discrete functions $S = \{s_i \mid i \in \{1,...,I\}\}$ in the form:

$$s_i(h) = round(\psi_i^{ss}(h\Delta t)),\ h \in \{\breve{N}^{\min},...,\breve{N}^{\max}\},$$
$$\breve{N}^{\min} = \breve{T}^{\min} / \Delta t,\ \breve{N}^{\max} = \breve{T}^{\max} / \Delta t,$$

where $round()$ is the function that rounds to the nearest integer.

Set of ECG signal patterns, which are located in a unified amplitude-time window, are formed.

3. Determination of quality criterion for ECG signal structuring

The work formulates the following quality criterion for ECG signal structuring, which means the choice of such a parameter γ that will deliver the minimum of the root-mean-square error:

$$F = \frac{1}{2I}\sum_{i=1}^{I}(\tilde{N}_i^{\min} - N_i^{\min})^2 + (\tilde{N}_i^{\max} - N_i^{\max})^2 \to \max_{\gamma}, \quad (1)$$

where $\tilde{N}_i^{\min}, \tilde{N}_i^{\max}$ are the boundaries of RR intervals of ECG signal set by the expert, $N_i^{\min}, N_i^{\max}$ – calculated boundaries of RR intervals of ECG signal.

4. Model for recognizing ECG signal patterns

Adaptive probabilistic neural network (APNN) based on multidimensional Gaussian functions is proposed as a model for recognizing ECG signal patterns, which allows identification of the structure and parameters and is defined in the following form:

$$y_j = \frac{1}{n_j}\sum_{i=1}^{K} I(z_i - j) G_i(\mathbf{x}),\ j \in \overline{1, N^{out}},$$

$$G_i(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^N \det \mathbf{C}_i}} \exp\left(-\frac{1}{2}(\mathbf{x} - \mathbf{m}_i)^T \mathbf{C}_i^{-1}(\mathbf{x} - \mathbf{m}_i)\right),$$

$$\mathbf{C}_i = \mathrm{diag}(\sigma_{i1}^2,...,\sigma_{iN}^2),$$

$$\det \mathbf{C}_i = \prod_{k=1}^{N} \sigma_{ik}^2,$$

$$n_j = \sum_{i=1}^{K} I(z_i - j),$$

$$I(a) = \begin{cases} 1, & a = 0, \\ 0, & else, \end{cases}$$

where w_{ij} are the weights, $\mathbf{m}_i$ is the vector of mathematical expectations of the N dimension of the i-th Gaussian function, $\mathbf{C}_i$ is the diagonal covariance matrix of the $N \times N$ dimension of the i-th Gaussian function, N is a pattern length, K is the number of Gaussian functions, N^{out} is the number of classes of RR interval, z_i is a marker of the class of RR interval of the i-th Gaussian function, $z_i \in \{1,...,N^{out}\}$.

5. Determination of quality criterion for recognizing ECG signal patterns

The work formulates the following quality criterion for recognizing ECG signal patterns, which means the choice of such a set of parameters Θ={ $w_{ij}, \mathbf{m}_i, \mathbf{C}_i$ }, that will deliver the maximum recognition probability:

$$F = \frac{1}{I}\sum_{\mu=1}^{I} I(\max_j y_{\mu j} - \max_j d_{\mu j}) \to \max_{\Theta}, \; j \in \overline{1, N^{out}}, \tag{2}$$

$$I(a) = \begin{cases} 1, & a = 0, \\ 0, & else, \end{cases}$$

where $\mathbf{d}_\mu$ is a binary vector, which is set by the expert for the μ-th pattern and corresponds to the number of the class of RR interval, $\mathbf{y}_\mu$ is a real vector, which is calculated by the model for the μ-th pattern and corresponds to the number of the class of RR interval.

6. Method for identifying the structure and parameters of the model for recognizing ECG signal patterns

Determination of the number of Gaussian functions of APNN is not automated and is performed by an operator based on his empirical experience. Therefore, in order to calculate the count and parameters of APNN, a clustering method with adaptive count of clusters (corresponding to Gaussian functions) is proposed, while the center of the first cluster is selected as a pattern of RR interval with a minimum distance to the remaining patterns. The author's adaptive clustering method includes the following steps:

1. Set a set of patterns of RR interval $S = \{s_i(n)\}$, $i \in \overline{1, I}, n \in \overline{1, N}$, which are in a unified amplitude-time window with length N and height L, where I is the count of patterns. Set a set of markers of classes of RR interval $Q = \{q_i\}$, $q_i \in \{1,...,N^{out}\}$, $q_i \leftrightarrow \mathbf{s}_i$, $i \in \overline{1, I}$, N^{out} is the count of classes of RR interval. Set the initial value of the parameter ε, $0 < \varepsilon < 1$. Set step $\Delta\varepsilon$, $0 < \Delta\varepsilon < 1$.
2. Calculate the normalized square of the distance between each pair of patterns of RR interval
$$D_{ij} = \frac{\|\mathbf{s}_i - \mathbf{s}_j\|^2}{NL^2}, \; i \in \overline{1, I}, \; j \in \overline{1, I}.$$
3. Calculate the distance between each pattern of RR interval and set of patterns of RR interval
$$d_i = \sum_{j=1}^{I} D_{ij}, \; i \in \overline{1, I}.$$
4. Determine the number of pattern of RR interval with the minimum distance
$$i^* = \arg\min_i d_i, \; i \in \overline{1, I}.$$
5. Set the pattern of RR interval with the minimum distance as a center of the first cluster ($\mathbf{m}_1 = \mathbf{s}_{i^*}$), set the zero matrix as the diagonal covariance matrix of the first cluster ($\mathbf{C}_1 = \mathbf{0}$), set the count of patterns of RR interval in the first cluster to one, i.e. $a_1 = 1$, set the marker of the class of RR interval pattern with the minimum distance as a marker of the first cluster, i.e. $z_1 = q_{i^*}$.
6. Set the count of clusters $K = 1$.
7. Set the count of pattern of RR interval $i = 1$.
8. If $i^* = i$, then go to step 15.
9. Calculate the normalized square of the distance between the *i*-th pattern of RR interval and centers of clusters
$$D_k = \frac{\|\mathbf{s}_i - \mathbf{m}_k\|^2}{NL^2}, \; k \in \overline{1, K}.$$
10. Calculate the smallest normalized square of the distance between the *i*-th pattern of RR interval and centers of clusters
$$d^* = \min_k D_k, \; k \in \overline{1, K}.$$
11. Determine the count of the cluster with the minimum distance
$$k^* = \arg\min_k D_k, \; k \in \overline{1, K}.$$

12. If $d^* \le \varepsilon$ and $z_{k^*} = q_i$, then calculate a new center of the k^*-th cluster, i.e. $\mathbf{m}_{k^*} = \dfrac{a_{k^*}\mathbf{m}_{k^*} + \mathbf{s}_i}{a_{k^*} + 1}$, calculate a new diagonal covariance matrix of the k^*-th cluster, i.e. $\mathbf{C}_{k^*} = \mathrm{diag}(\boldsymbol{\sigma}^2_{k^*})$, $\boldsymbol{\sigma}^2_{k^*} = \dfrac{a_{k^*}\boldsymbol{\sigma}^2_{k^*} + \left(\mathbf{s}_i - \mathbf{m}_{k^*}\right)\left(\mathbf{s}_i - \mathbf{m}_{k^*}\right)^T}{a_{k^*} + 1}$, increase the count of patterns of RR interval in the k^*-th cluster, i.e. $a_{k^*} = a_{k^*} + 1$.
13. If $d^* > \varepsilon$, then set the *i*-th pattern as the center of a new cluster; i.e. $\mathbf{m}_{K+1} = \mathbf{s}_i$, set the zero matrix as a diagonal covariance matrix of a new cluster, i.e. $\mathbf{C}_{K+1} = \mathbf{0}$, set the count of patterns of RR interval in the new cluster to one $a_{K+1} = 1$, set the marker of the class of the *i*-th pattern as the marker of a new cluster, i.e. $z_{K+1} = q_i$, increase the count of clusters, i.e. $K = K + 1$.
14. If $d^* \le \varepsilon$ and $z_{k^*} \ne q_i$, then decrease the value of ε parameter, i.e. $\varepsilon = \varepsilon - \Delta\varepsilon$, go to step 6.
15. If $i < I$, then go to a new pattern ($i = i + 1$), go to step 8.

The count, parameters and markers of cluster classes, which correspond to the Gaussian functions of APNN, are determined.

7. Determination of characteristics and quality criterion of identification of the structure and parameters of the model for recognizing ECG signal patterns

To evaluate the clustering method, which makes it possible to calculate the count and parameters of radial basis functions of APNN, the following characteristics are used in the work:

1. The probability of false clustering means the ratio of the count of clusters that contain patterns of different classes to the total count of clusters

$$P = \frac{V}{K},$$

where V is the count of clusters that contain patterns of different classes, K is the total count of clusters.

2. Compression ratio

$$C = \frac{I}{K},$$

where I is the count of patterns, K is the total count of clusters.

Based on the probability of false clustering and the compression ratio, the following criterion for the quality of clustering:

$$F = P + \frac{1}{C} \to \min_{\varepsilon}, \tag{3}$$

is formulated, which means the choice of such a value ε that gives the minimum to the sum of the clustering probability and the reciprocal of the compression ratio.

8. Numerical study of the method for structuring and transforming the ECG signal

For ECG signals, the sampling frequency $f_d = 360Hz$, the count of quantization levels $L = 2048$ were set. Window length $N = 512$.

As a result of a numerical research of the method for ECG signal structuring with the parameter $\gamma = 0.5$ for ECG signals of the people from the MIT-BIH Arrhythmia database, according to criterion (1), a root-mean-square error of 0.02 was calculated.

Figs. 1-3 show an initial ECG signal (Fig. 1) with the definition of the boundaries of RR intervals of ECG signal (Fig. 2) and geometric converts of RR intervals of ECG signal to a unified amplitude-time window (Fig. 3).

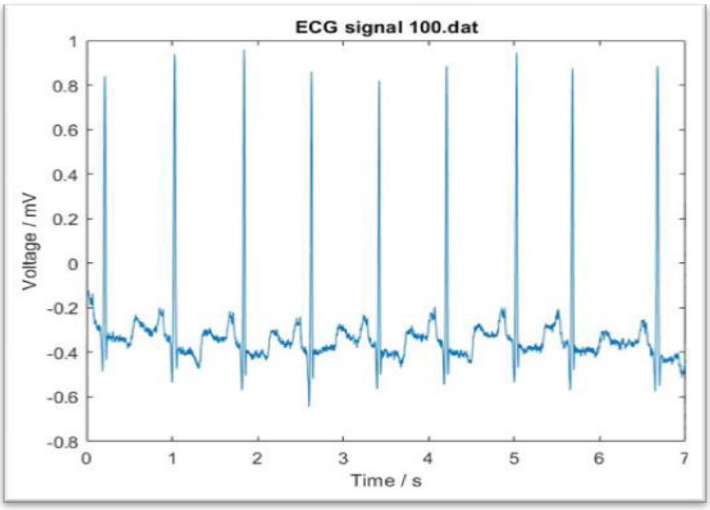

Figure 1: Initial ECG signal (11-bit, 360 *Hz*, length 2521).

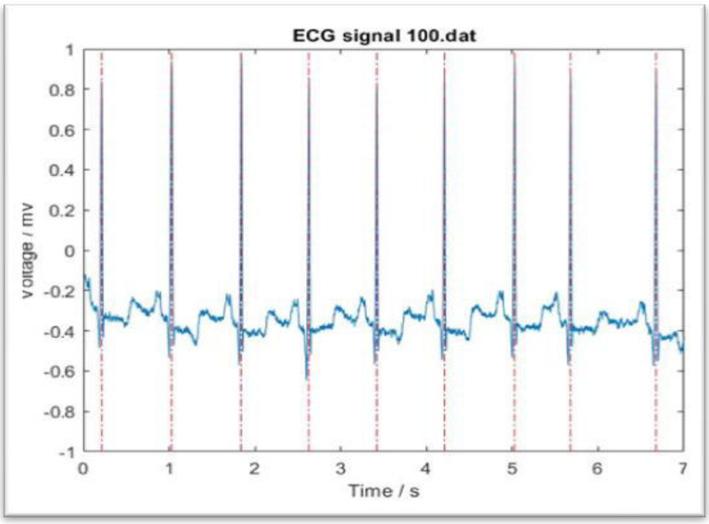

Figure 2: ECG signal after marking the boundaries of RR intervals (parameter $\gamma = 0.5$).

9. Numerical research of the method for identifying the structure and parameters of the model for recognizing ECG signal patterns

For ECG signals, the sampling frequency $f_d = 360Hz$, the count of quantization levels $L = 2048$ were set. Window length $N = 512$.

As a result of a numerical research of the clustering method, which allows to determine the number, parameters and markers of classes of Gaussian functions of APNN, with the parameter $\varepsilon = 0.001$ for ECG signals of the people from the MIT-BIH Arrhythmia database, according to criterion (3), the compression ratio of $C = 2$ and the probability of false clustering $P = 0$ were obtained.

Fig. 4 shows an example of a previously structured ECG signal marked with cluster numbers (Fig. 3). In this case, the clusters with numbers 1, 2, 3 correspond to one class (normal heartbeat), and the cluster with number 4 corresponds to another class (atrial premature heartbeat), i.e. $z_1 = \{1, 2, 3\}$, $z_2 = \{4\}$.

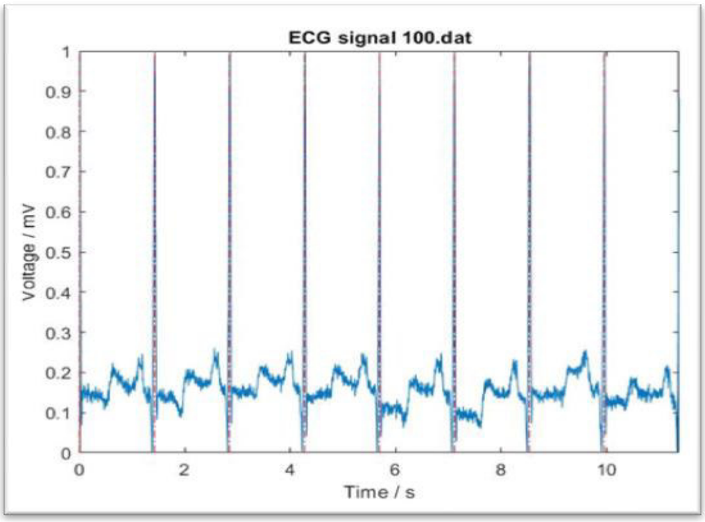

Figure 3: ECG signal after geometric converts of RR intervals to a unified amplitude-time window.

10. Numerical study of the model for recognizing ECG signal patterns

Table 1 shows the probabilities of recognizing ECG signal patterns obtained on the basis of the MIT-BIH Arrhythmia based on artificial neural networks according to criterion (2). At the same time, multilayer perceptron had 2 hidden layers (each consisted of 512 neurons, like the input layer), and the neural network based on radial basis functions had one hidden layer (consisted of 1024 neurons, like the input layer).

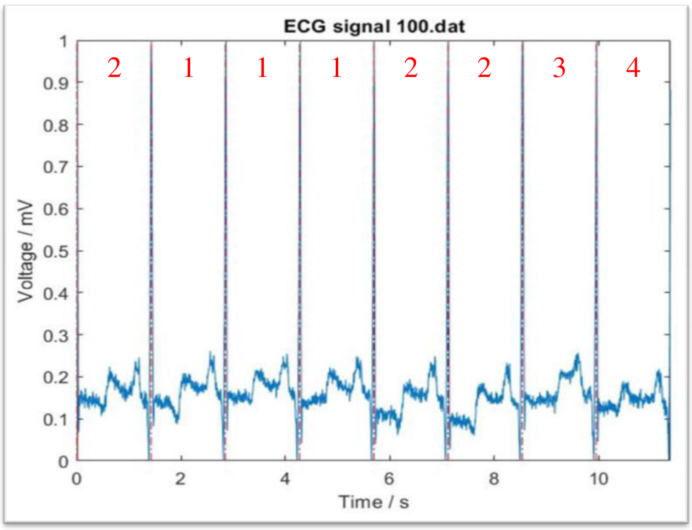

Figure 4: ECG signal after clustering (parameter $\varepsilon = 0.001$).

Table 1
Probability of recognition of ECG signal patterns

Artificial neural network	Recognition probability
Multilayer perceptron	0.80
Neural network based on radial basis functions	0.85
Support vector machine	0.9
Proposed adaptive probabilistic neural network	**0.98**

According to Table 1, the proposed adaptive probabilistic neural network gives the best results.

11. Conclusions

1. To solve the problem of increasing the quality of ECG diagnostics, the corresponding methods of ECG signal pre-processing, such as calculation of the length of RR interval and signal transformation, as well as methods for identifying the structure and parameters of the model for recognizing RR intervals of ECG signal have been investigated.
2. A method for structuring and transforming an ECG signal has been proposed, which consists: calculation of the length of RR interval of ECG signal based on statistical estimation of local maximum and band-pass filtering, which decreases the computational complexity and decreases the dependence on noise and permits to use dynamic threshold, which increases the accuracy of calculating the length and boundaries of RR intervals; geometric transformation of RR interval of ECG signal, which makes it possible to transform RR intervals to a unified amplitude-time window, which permits to form patterns of ECG signal on basis its structure.
3. A model for recognizing an ECG signal based on adaptive probabilistic neural network, which allows identification of the structure and parameters, is proposed, which increases the recognition probability.
4. A method for determining the structure and parameters of the model for recognizing ECG signal patterns, which is based on adaptive clustering, is proposed, which provides a high degree of compression and clustering of ECG signal patterns.
5. A numerical study of the method of structuring and transforming the ECG signal, which allowing to evaluate the proposed method, has been carried out.
6. A numerical research of the method for identifying the structure and parameters of the model for recognizing ECG signal patterns, which allows to evaluate the proposed method, has been carried out.
7. A numerical research of the model for recognizing ECG signal patterns, which makes it possible to evaluate the efficiency of the proposed model (the recognition probability has increased to 0.98), has been carried out.
8. The proposed methods and model make it possible to formulate and solve the problems of structuring, transforming and recognizing the ECG signal, which is used for ECG diagnostics.

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