The neuronet method for pulse wave analysis by hydro-cuff technology at cardiovascular system diagnosis

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Abstract. The article discusses the application of intelligent neural networks for the diagnosis of diseases. The use of a neural network for the diagnosis of cardiovascular diseases is justified. The advantages and disadvantages of existing methods for analyzing the pulse wave circuit are considered. The increase in the accuracy of calculating the critical points of the pulse wave is justified. To increase the accuracy, a hydro-cuff technology has been proposed, which can significantly increase the amplitude of oscillations caused by pulsation of arteries. A neural network has been developed to detect the characteristic points of pulse signals recorded using hydro-cuff technology. Setting the coefficients of neural network cascade-correlation is performed using iterative Kachmazh’s algorithm. Signal processing was performed in the MatlabR2017b environment.

1. Introduction

The diagnosis and treatment high-tech methods implementation will allow to provide the most complete medical care to the population with diagnoses associated with cardiovascular system disease.

Currently, artificial neural networks (ANN) are beginning to be used in various areas of diagnostic medicine such as oncology, cardiology, and pulmonology. Neural network technologies are used to diagnose hepatitis [1], diabetes [2,3], gastrointestinal tract diseases [4], spine and bone system [5], as well as work in the neurology field [6] and psychology [7]. ANN has proven its effectiveness in the cardiovascular diseases diagnostics. Special attention is paid to the ANN using for the coronary heart disease diagnosis. Thus, A. G. Shooev and the study [8] showed that the developed and trained neural network is applicable for the coronary heart disease diagnosis. The obtained coronary atherosclerosis and coronary heart disease diagnostics reliability was 96 and 94 %, respectively. O. Yu. Atkov, S. G. Gorokhova et al. in the study [9] several neural network systems developed, the reliability of which varied from 64 to 94 %. Similar parameters (95.5 %) for diagnosing coronary heart disease were obtained by H. Niranjana Murphey and M. Meenakshi by the other study [10]. H. Moghaddasi et al. in the research [11] a multi-layer perceptron was used as a neural network model for diagnosing heart ischemia, which was trained using the Broyden–Fletcher–Goldfarb-Shanno (BFGS) algorithm. The materials on the neural network methods use for analyzing pathological changes in blood vessels [12] and predicting the arterial hypertension risk developing [13]. The materials [14] describe the mechanism...
of applying similar methods for automatic analysis of electrocardiograms in the cardiovascular system diseases diagnosis. The review of the materials published has shown the prospects of using ANN in new areas of clinical diagnostics. It is also possible to acknowledge the possibility of developing an artificial neural network for automatic analysis of the pulse wave signal recorded using hydrocuff technology.

2. Materials and methods

The study purpose is to create neural networks for detecting characteristic points of pulse signals captured by using hydrocuff technology [15], determining the cardiovascular system abnormalities and identifying the corresponding disease, in particular atherosclerosis. Early diagnosis is often a decisive factor in the positive outcome of the patient's disease. The modern diagnostic and laboratory equipment development has significantly increased the accuracy of diagnostics in cardiology.

In broad terms, the pulse wave signal is a curve recorded using a technical tool, caused by an increase in pressure spreading through the aorta and arteries, as a result of the blood release from the left ventricle during systole.

In materials on human physiology [16], it is claimed that the pulse wave occurs at the aorta mouth during the expulsion of blood into it by the left ventricle. To accommodate the blood shock volume, the systolic pressure, aortic diameter, and its volume increase.

During ventricular diastole, due to the elastic properties of the aortic wall and the outflow of blood from it to the peripheral vessels, the vessel volume and diameter are restored to its original size. During ventricular diastole, due to the elastic properties of the aortic wall and the outflow of blood from it to the peripheral vessels, the volume and diameter of the vessel are restored to their original size. It follows that the pulse wave form stores a number of hemodynamics vital indicators: blood shock volume, systolic and diastolic pressure, the pulse wave speed propagation, blood viscosity, the blood vessels elasticity degree.

The pulse wave (PW) shape is influenced by many factors, such as the technical means of recording, the place where the signal is taken, the patient age, the cardiovascular system pathologies presence or absence. The pulse wave signal is an information source that can inform about the actual human cardiovascular system state, without resorting to expensive research. Since this process is unique to a living organism, various metastatic models of oscillation formation in a vessel are used to understand the mechanism [17,18]. Currently, a large number of medical systems have been developed that allow recording the PW signal non-invasively and in real time with varying accuracy [19].

Figure 1 shows the pulse wave recorded by the "Hemodyn1" hydrocuff device. The experimental sample was developed at the Department of "Medical Cybernetics and Informatics", Medical Institute of Penza state University in colaboration with the scientific enterprise "Promed".

![Figure 1. Pulse wave recorded by the hydrocuff device «Hemodyn 1»](image)

The pulse wave curve is a quasi-periodic signal; it has a strict periodicity only in absolutely healthy people.

Informative parameters of pulse curves recorded using hardware and software systems such as "Hemodyn1" can be divided into several categories. Primary (amplitude, time, and frequency). The
amplitude–frequency characteristics (AFC) can be extracted from the entire recorded signal or individual oscillations. Features obtained by mathematical operations, as well as statistical indicators that evaluate the dynamics of changes in different parameters over time, store informative material.

The pulse wave nature depends on the systolic output, the blood flow intensity, blood viscosity, and the vascular walls state. [19] describes all the components of the pulse wave. It is described which section is responsible for the operation of the "heart – vessels" system.

The calculation and analysis of the values of the first and second derivatives of the pulse wave signal registered using hydrocuff technology is associated with certain difficulties caused by the significant influence of noise, motion artifacts, and pressure reduction during decompression. In addition, the assessment of pressure pulsations occurs in the range of 10-20 mmHg, in case a pressure in the cuff from 300 to 60 mmHg. In the aggregate, these processes have a significant impact on the values of the first and second derivatives. Their changes, function increments at each step of digitization have increments commensurate with the changes in the function. In this regard, it is necessary to implement special methods that reduce the error of fixing characteristic points on the pulse wave contour. The paper uses the spline interpolation method based on changing the position of the characteristic points of the selected fragment of the curve. Signal processing was performed in the MatlabR2017b environment.

![Figure 2. Projections of the differential curve and the initial pulse wave curve.](image)

Figure 2 shows the source signal and first-and second-order derivatives with normalized values and coefficients for clarity. For the first derivative, the coefficient is assumed to be five. For the second derivative, the coefficient is fifty. The coefficient determines the steepness of the derivatives’ amplitudes.

The pulse wave contour must be analyzed by the first and second derivative of the signal from time. Issues of pulse wave contour analysis, characteristic points determining, hemodynamic parameters calculations, relevant pathologies diagnosis are mentioned in [20, 21, 22, 23] from this can be concluded that the purer the initial signal, the more accurate will be allocated its principal components, the calculated points of the signal extremum and as a consequence the values characterizing the cardiovascular system in general. The pulse wave signal recorded using hydrocuff technology [15] can significantly increase the oscillations amplitude, improve the signal-noise characteristics, and thereby improve the quality of the PW contour representation. Hydrocuff technology provides a unique opportunity to generate large amounts of data and apply automatic analysis to the images recognition of various types of cardiovascular system pathologies. The PW automatic analysis obtained on the basis of hydrocuff technology has not been performed before. Therefore, it requires solving a number of theoretical and practical problems. One of the possible solutions is the use of a multi-layer neural network. However, the choice of topology is complicated by the search for the most optimal solution to the task of the pulse wave signal contour analysis.

Based on the review, a neural network modular formation method is proposed in fact, modules of divided neural networks of cascading correlation interact inside, which build their architecture to solve the problem in the best possible way.
The proposed method for constructing a modular neural network, which is applied to cascade correlation networks, is shown in figure 3.

The key idea is in the distribution of objects in units at each level is estimated by connecting to adjacent levels.

As shown in figure 3 a partial network consisting of connections between each level and its adjacent levels is represented as two matrix: $A^d = \{ A_{ij}^d \}$ and $B^d = \{ B_{ij}^d \}$. The $A^d$ and $B^d$ matrix represent connections between two depth layers $d-1$ and $d$ and two depth layers $d$ and $d+1$ respectively.

The $A_{ij}^d$ element is set as

$$ A_{ij}^d = \begin{cases} 1 & (|w_{ij}^d| \geq \xi) \\ 0 & \text{(remaining)} \end{cases} $$

where $\xi$ hyper parameter to exclude influence coefficient. Similarly the $B_{ij}^d$ element set as (1)

$$ B_{ij}^d = \begin{cases} 1 & (|w_{ij}^d| \geq \xi) \\ 0 & \text{(remaining)} \end{cases} $$

As shown in figure 4, the community discovery statistical model has three types of parameters. These parameters are normalized so that they meet the following conditions:

$$ \sum_c \pi_c = 1, \quad \sum_i \tau_{c,i} = 1, \quad \sum_i \tau'_{c,i} = 1. $$

The problem is to find the parameters $\pi, \tau, \tau'$ that maximize the probability of the given matrix $A, B$. The first parameter $\pi=\{\pi_c\}$ represents the a priori probability of unit in the layer of depth $d$, which belongs to the community $c$. The conditional probability of joining for a given community $c$ is represented by the second and third parameters $\tau=\{\tau_{c,i}\}$ and $\tau'=\{\tau'_{c,i}\}$, where $\tau_{c,i}$ represents the probability that a connection to a unit in community $c$ is attached from the $i$-th block to the depth of the $d-1$ layer. Similarly, $\tau'_{c,i}$ represents the probability that a connection from a unit in community $c$ is attached to a $j$-th unit at depth level $d+1$. Here the index $d$ in the parameters $\pi, \tau, \tau'$ is omitted for simplicity.

3. Results

The algorithm for finding optimal parameters $\pi, \tau, \tau'$ can be described as follows. First: the assignment of the community $g=\{g_k\}$, is entered, where $g_k$ is the community of the $k$-th unit in the depth layer $d$.

Parameters are optimized so that they maximize the probability of $A, B$ and $g$:

$$ A, B, g | \pi, \tau, \tau' = Pr(A, B|g, \pi, \tau, \tau') Pr(g|\pi, \tau, \tau'). $$

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**Figure 3.** Trained neural network.  
**Figure 4.** The community detection mechanism.
where
\[
Pr(A, B, g | \pi, \tau, \tau') = \prod_k \{ \prod_i (\tau_{gk,i})^{A_{ik}} \} \{ \prod_j (\tau'_{gk,j})^{B_{kj}} \},
\] (5)
\[
Pr(g | \pi, \tau, \tau') = \prod_k \pi_{gk}.
\] (6)

Then the logarithmic probability of \( A, B \) is given by
\[
\zeta = \ln Pr(A, B, g | \pi, \tau, \tau') = Pr(A, B | g, \pi, \tau, \tau') Pr(g | \pi, \tau, \tau') = \sum_k \{ \ln \pi_{gk} + \sum_i A_{ik} \ln \tau_{gk,i} + \sum_j B_{kj} \ln \tau'_{gk,j} \}.
\] (7)

The parameter \( g \) in (7) is a hidden variable and is unknown in advance, so the expected logarithmic likelihood \( \bar{\zeta} \) over \( g \) is calculated:
\[
\bar{\zeta} = \sum_{k,c} q_{k,c} \{ \ln \pi_c + \sum_i A_{ik} \ln \tau_{c,i} + \sum_j B_{kj} \ln \tau'_{c,j} \}.
\] (8)

The \( q_{k,c} \) parameter represents the probability that the \( k \)-th unit is assigned to the \( c \) community. If \( \{q_{k,c}\}, \{\pi_c\}, \{\tau_{c,i}\}, \{\tau'_{c,j}\} \) maximize \( \bar{\zeta} \) in (8), then they satisfy
\[
q_{k,c} = \frac{\pi_c \prod_i A_{ik}^{A_{ik}} \prod_j B_{kj}^{B_{kj}}}{\sum_s \pi_s \prod_i A_{is}^{A_{is}} \prod_j B_{sj}^{B_{sj}}}, (\forall k, c)
\] (9)
\[
\pi_c = \frac{\sum_k q_{k,c}}{\sum_c \sum_k q_{k,c}}
\] (10)
\[
\tau_{c,i} = \frac{\sum_k q_{k,c} A_{ik}}{\sum_k q_{k,c} A_{ik}}
\] (11)
\[
\tau'_{c,j} = \frac{\sum_k q_{k,c} B_{kj}}{\sum_k q_{k,c} B_{kj}}, (\forall c, i, j)
\] (12)

From the calculations above, the optimal parameters \( \pi, \tau, \tau' \) and the probability of determining \( g \) for the optimized parameters are iteratively estimated based on equations (11) and (12), which is defined by \( c \), which maximizes \( q_{k,c} \). Figure 5 shows the community structure. The next stage is to define a modular representation of a layered neural network that summarizes typical connections between modules figure 6 at which the modular representation defines related connections that add up a set of connections between neurons.

![Figure 5. Formed community structure.](image)

![Figure 6. A neural network modular representation.](image)

The described algorithm allows for self-organization of the network, which is divided into two stages:

- self-organization of individual modules of the cascade correlation neural network;
- self-organization of relations between modules for the final topology.
A modular neural network reduces the dimension of the neural network for a specific task. A complex task requires the use of cascade correlation neural networks as a module. The final stage of training consists in such a selection of influence coefficient, in which the correlation between the activity of the added neuron and the error value at the network output is maximized and determined by the correlation coefficient $S$.

\[ S = \sum_{j=1}^{M} \sum_{k=1}^{p} (v^{(k)} - \bar{v})(e_j^{(k)} - \bar{e}_j), \]  

(13)

where $p$ – is the number of training samples, $M$ – number of output neurons $v^{(k)}$ – output signal of the neuron-candidate for $k$-th training sample, $e_j^{(k)}$ – value of error of the $j$-th hidden neuron to the $k$-th training sample, $\bar{v}$ and $\bar{e}_j$ – average values.

After reaching the maximum value of $S$, the candidate neuron is included in the network structure, the calculated coefficients - of its connections are fixed, and the process of selecting the coefficients of output neurons to minimize the target function continues. Training occurs simultaneously for several of the neurons-candidates. The General topology of forming a cascade correlation network based on the modular principle is shown in figure 7.

![Figure 7. The obtained network architecture.](image)

Setting the coefficients of neural network cascade-correlation is performed using iterative Kachmazh’s algorithm. The solution method is described in detail in [1]. The iterative Kachmazh’s method is difficult to predict based on convergence results, to solve this error, the introduction of a relaxation parameter $\mu$ to the algorithm is proposed.

In this case, the iterative sequence will take the form

\[ u_k^i = u_k^{i-1} + \mu \cdot A_i^T \cdot \frac{L_i - (A_i u_k^{i-1})}{\|A_i\|^2}. \]  

(14)

Where $i=1...n$, $k=1...m$,

\[ u_k^0 = u_k^n \]  

(15)

The considered algorithm is used for calculating influence coefficients in a modular neural network.

4. Conclusion

In the system training process, the studies of systems training methodology needed for efficiency increase were performed: the effect of training samples amount on the system accuracy, the influence of tolerance error training on the accuracy of the response interpretation and the learning rate, and determines the methods of forming the training samples, the effect of normalization of factors values on the system reliability. The method research of forming a training sample to determine the patient's condition was conducted. The designed training sample consists of 55 examples for 5 patient’s states.
As a result of the research, an algorithm for training a neural network using natural data is presented. The neural network architecture was developed.

The experiment results showed that artificial neural networks can act as an additional method for early cardiovascular diseases diagnosis and help the doctor in making a diagnosis. The proposed neural network training algorithm makes it possible to get a solution at the disease early stages. The paper proposes an approach to create a decision support system for identifying various cardiovascular diseases forms and monitoring the therapy effectiveness, with the rational treatment strategy choosing possibility. The neural network use for the pulse wave shape contour analysis will eventually improve the quality of determining various pathologies of the circulatory system. The introduction of data mining technology and neural network training based on cascading correlation of multidimensional data allows for faster and more accurate diagnoses prediction in the field of cardiovascular diseases. The proposed algorithm for constructing and training a modular neural network based on the adaptive recurrent iterative Kachmazh’s algorithm, which, unlike competing algorithms, adjusts the internal topology to a specific task, and also allows reducing the complexity of training a neural network by 7%, increasing the reliability of recognizing cardiovascular pathology to 94.3% and assessing the state of severity to 90.3%.

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