Multimodal neural network classifier of the functional state of the respiratory system

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Abstract. At present, the intelligent systems are used to study the functional state of living objects. They are often built on a multimodal basis, i.e. decision-making is carried out through several information channels with the subsequent aggregation of these decisions. In the proposed method, the electrocardiosignal is a source of information. The principle of multimodality is implemented by analyzing of various methods and aggregating the results using neural networks of block and hierarchical structure. The method was tested on the classification of patients with pneumonia with a clear diagnosis. A group of volunteers without pulmonary pathologies was used as an indifferent class.

An electrocardiosignal (ECS) is often used to study biorhythms in a living organism. The ECS is unique from the point of view that many waves in organism can modulate this signal as waves of a higher order.

For example, in [1], the ECS wave structure is used to classify seven types of arrhythmias using deep convolutional neural network (DCNN) models. The developed arrhythmia classifier allowed cardiologists, based on the results of ECG interpretation, to significantly reduce the number of erroneous diagnoses. The best DCNN model provides a diagnostic sensitivity of 95.43% and a diagnostic specificity of 96.75%.

Currently, multimodal approaches are widely used in the study of the state of a complex biological object. They suggest using the results of monitoring several biological signals or several methods of their analysis to classify of a living system’s condition. The research results presented in [2] are an example of such an approach. A neural network classifier of sleep stages based on the analysis of SpO2 patterns and heart rate is described in this article.

The cardiorespiratory system, consisting of the cardiovascular system (CVS) and the respiratory system (RS), is the most sensitive indicator of the physiological state of the body. Therefore, the development of methods for the classification of the functional state (FS) of this system based on the descriptors obtained in the process of analyzing the dynamics of the interaction of CVS and RS over a certain period of time is an urgent line of research [3, 4]. Indicators of synchronicity of cardiac, vascular and respiratory rhythms, which reflect the level of adaptation of the body under exogenous influences, are important diagnostic indicators of the functional state of the cardiorespiratory system. [5, 6, 7].
We believe that when constructing descriptors for classifiers of respiratory system’s functional state, the main relevant information is concentrated in slow waves [8]. Therefore, the problem of the formation of the feature space is reduced to the selection of slow waves in the signal under study and their adequate description in the generated space of informative features.

The respiration rhythm (RR) can be observed on the spectral characteristics of the electrocardiosignal (ECS) in the form of a wave train in the frequency range from 0.15 to 0.4 Hz [5]. The amplitude Fourier spectrum of the ECS is shown in figure 1. In this figure, trains of systemic rhythms corresponding to frequency ranges in the region of slow waves are highlighted [1, 6].

![Figure 1. Amplitude Fourier spectrum of an electrocardiosignal recorded for three minutes with a sampling rate of 200 Hz.](image1)

Electrophysiological signals used to identify systemic rhythms are not stationary at the observed intervals; therefore, Fourier analysis does not allow the formation of descriptors for a reliable classification of the functional state of the respiratory system. In this case, we recommend using time-frequency analysis, in particular, wavelet analysis. Considering that the wavelet plane of the electrocardiosignal reflects both the rhythms of the cardiovascular system and the rhythms of the respiratory system, then to obtain descriptors of the functional state of the respiratory system, we use the lines of the wavelet plane of the electrocardio signal belonging to the frequency range of the respiratory rhythm (RR) [8]. We use the indicators of the variability of these lines in time and frequency as descriptors for the trained classifier of the functional state of the breathing system. This classifier is based on a multilayer forward propagation neural network [9, 10].

In figure 2, one of the sections of the ECS wavelet plane along the frequency axis (on the wavelet plane this is the vertical axis) is shown. The wavelet transform parameters are selected so that the full frequency range includes frequencies from 40 Hz to 0.08 Hz. Each systemic rhythm has its own frequency range, just like in figure 1.

![Figure 2. Diagram of one column of the wavelet plane of the electrocardiosignal.](image2)

In each frequency train in figure 2, the frequency variation in the lines of the wavelet plane forming this train is reflected. The analysis of these frequency components showed that the wavelet-plane trains,
the lines of which lie in the region of the breathing rhythm, correspond to wavelengths with periods of 20 ... 30 seconds, which allows us to refer them to the range of very low frequencies (VLF). The trains exist with frequencies in the range between heart rate and respiration rates. They reflect slow waves of the first order, to which, as a rule, a systemic rhythm of about 0.1 Hz corresponds. The construction of descriptors for "weak" classifiers for these trains is reduced to determining the Fourier spectrum of the corresponding train.

In the classifier of the functional state of the respiratory system, we use the hierarchical structure of the neural network, which includes three autonomous neural networks NET1, NET2 and NET. NET1 and NET2 networks have two outputs, which show the probability of finding the respiratory system in a given functional state and the probability of finding the respiratory system in an indifferent class. NET network aggregates the solutions of the first two networks on both outputs. The structural diagram of the neural network classifier of the functional state of the respiratory system is shown in figure 3.

Variability indices of the selected lines of the wavelet plane in time (shift) are used as descriptors of the neural network NET1. Variability indicators of the selected lines of the wavelet plane in frequency (in scale) are used as descriptors of the neural network NET2.

We form an $L \times N$ matrix of wavelet-plane rows lying in the frequency range of the breathing rhythm to calculate descriptors of the neural network NET1. Here $L$ is the number of rows of the wavelet plane of the pacemaker, lying in the range of the breathing rhythm. And $N$ is the number of columns of the wavelet plane, which is determined by the number of samples of the ECS. We determine the Fourier spectra of the rows of the resulting matrix $\{f_{\ell k}\}, \ell = 1, L$, $k = 1, N$, next select from the $N$ spectral Fourier coefficients in each of the $L$ rows of the matrix $M$ coefficients $f^{*}_{\ell m}$ corresponding to the VLF range of the ECS spectrum [6], next determine the first differences of these coefficients by rows and calculate the set of descriptors for NET1 $\{d_{1j}\}, j = 1, M$ like

$$d_{1j} = \sum_{\ell=2}^{L} |f_{\ell j}^* - f_{\ell-1, j}^*|.$$  \hspace{1cm} \text{(1)}$$

We use the same $L \times N$ matrix of wavelet coefficients $\{w_{\ell m}\}, \ell = 1, L$, $n = 1, N$, formed from wavelet plane rows lying in the region of respiration rhythm frequencies to calculate descriptors of the second neural network. We transpose the resulting matrix of wavelet coefficients into the $N \times L$ matrix, then in each of the $N$ rows of the transposed matrix we find the maximum wavelet coefficient in absolute value, then we determine the row number of the transposed matrix to which this wavelet coefficient belongs, then we form a variation series of $N$ row numbers of this transposed matrix. Elements of this variation series are defined as

$$d_{2n} = \arg\left[\max_{\ell=1,L}(|w_{\ell n}|)\right],$$  \hspace{1cm} \text{(2)}$$

then we determine the spectrum of the obtained variation series

$$f d_{2k} = \sum_{n=1}^{N} d_{2n} \cdot \exp(-2\pi kn / N)$$  \hspace{1cm} \text{(3)}$$

then we select from the set $\{f d_{2k}\}, k = 1, N$ a set of spectral coefficients $\{f d_{2k}^*\}, k = 1, \Theta$ lying in the VLF range of the ECS spectrum [4], and then use the values of the elements of this set as descriptors of the neural network NET2.
The functional state of the respiratory system is classified as follows. The sensors of the pneumograph and electrocardiograph are connected to the patient. Their signals are digitized and fed to a computer. The spectral range of the pneumogram is determined after obtaining a synchronous recording of files with a given number of samples [5]. The program module "frequency selector" selects the frequency range in which the main energy of the pneumogram spectrum lies and transfers the boundaries of this range to the module for generating descriptors. The wavelet transform of the ECS is defined in the "wavelet analysis" module.

We used the frequency range of the breathing rhythm to determine the indicators of the variability of the breathing rhythm on the wavelet plane of the ECS. Since the frequency range of the breathing rhythm is unique for each individual, the Fourier spectrum of the pacemaker was calculated to determine it, and the spectral composition of its train belonging to the breathing rhythm was analyzed. We calculated the parameters for constructing the ECS wavelet plane based on the frequency range of this train.

We calculate the descriptors of the neural network NET 1 by forming a matrix of wavelet coefficients of size LxN, located in the breathing rhythm region, and calculating the Fourier spectra in the rows of this matrix. As a result, the set of wavelet coefficients \( \{w_{\ell n}\}, \ell = 1, L, n = 1, N \) is transformed into a set of Fourier coefficients \( \{f_{\ell k}\}, \ell = 1, L, k = 1, \bar{N} \), where

\[
f_{\ell k} = \sum_{n=1}^{N} w_{\ell n} \cdot \exp(-2\pi kn/N)
\]

(4)

Next, we carry out the selection of the columns of spectral Fourier coefficients of the rows of the wavelet plane, as a result of which in each row we select M spectral Fourier coefficients (belonging to the VLF range) from N spectral coefficients. The spectral coefficient matrix is converted from LxN to LxM with elements \( \{f'_{\ell m}\}, \ell = 1, L, m = 1, M \).
As a result, we can determine the frequency variation of the Fourier spectrum in the form of the first
differences of the elements along the rows of the $L \times M$ matrix

$$
\Delta \ell_m = f_{\ell,m} - f_{\ell,m-1}, \quad m = 2, M.
$$

(5)

We calculate descriptors for NET 1 by the formula

$$
d_1m = \sum_{\ell=2}^{L} |\Delta \ell_m|.
$$

(6)

We calculate the descriptors of the neural network NET2 by analyzing the lines of the wavelet plane
located in the breathing rhythm region, that is, based on the analysis of the matrix of wavelet coefficients
$\{w_{\ell,n}\} \quad \ell = \overline{1, L} \quad n = \overline{1, N} \quad \text{of size} \ L \times N$. This matrix is transformed, as a result of which we get a matrix of
wavelet coefficients $\{w_{n,\ell}\} \quad n = \overline{1, N} \quad \ell = \overline{1, L} \quad \text{of size} \ N \times L$.

We find the maximum in absolute value wavelet coefficient and determine the row number of the
transposed matrix to which this wavelet coefficient belongs in each of the $N$ rows of the transposed
matrix. As a result of this procedure, we form a variation series of $N$ numbers of columns of the
transposed matrix, the elements of which are determined according to (2). The value of an element of
the variation series is determined by the maximum wavelet coefficient in absolute value. The element
of the variation series is assigned the value of the number of the column of the transformed matrix, in
which the maximum element is located.

The spectrum $\{f_{d2k}\} \quad k = \overline{1, N}$ of the obtained variation series is determined according to (3). From
the set $\{f_{d2k}\} \quad k = \overline{1, N}$, we select a set of spectral coefficients lying in the VLF range, and use the
values of the elements of this set as descriptors of the neural network NET2.

We formed training samples based on clinical studies of $S$ patients whose respiratory system was in
one of two classes of functional states, one of which is indifferent. The table "object - feature" for the
neural network NET is formed after training all neural networks of the first hierarchical level. The
training sample for training the neural network NET is formed from the outputs of the neural networks
NET1 and NET2 according to table 1.

**Table 1.** Data format for the "object-feature" table for training the neural network NET.

| NN samples | Output NET1 | Output NET2 | Goal |
|------------|-------------|-------------|------|
|            | $P1$ | $P1$ | $P2$ | $P2$ | $P$ | $P$ |
| 1          | $NET_{11}$ | $NET_{11}$ | $NET_{21}$ | $NET_{21}$ | 1 | 0 |
| 2          | $NET_{12}$ | $NET_{12}$ | $NET_{22}$ | $NET_{22}$ | 0 | 1 |
| S          | $NET_{1S}$ | $NET_{1S}$ | $NET_{2S}$ | $NET_{2S}$ | 1 | 0 |

As an example, we took a group of patients with pneumonia with a clearly defined diagnosis (X-ray,
X-ray tomography, laboratory analysis data) and a group of volunteers without pulmonary pathologies.
Diagnoses were coded with the characters "0" and "1". The control samples were formed from the
obtained training sample by the rolling exam method. The space of informative features was determined
for each neural network of the NET1 and NET2 group by means of definitions (6) and (3).
We chose such parameters as diagnostic sensitivity (DSn), diagnostic specificity (DSP) and diagnostic efficiency (DE) as indicators of the diagnostic quality of the proposed classifier. We compared the indicators both with the prototype and with the indicators of the quality of X-ray studies on the same control sample. Indicators of the quality of diagnostics for the classes "pneumonia - no pneumonia" for one of the control samples are presented in table 2.

Analyzing table 2, we came to the conclusion that on this control sample, both methods of classifying the functional state of the respiratory system have practically the same diagnostic efficiencies.

Table 2. Indicators of the quality of predicting the functional state of the respiratory system in the control sample.

| The surveyed | Classifier | Based on the analysis of the variability of slow waves of the VLF range | X-ray examinations |
|--------------|------------|------------------------------------------------------------------------|--------------------|
| n_{p1}^{1} = 60 | DSn | 76% | DSn |
|              | DSP | 82% | DSP |
|              | DE  | 79% | DE  |
| n_{p2}^{2} = 60 | DSn | 82% | DSn |
|              | DSP | 76% | DSP |
|              | DE  | 79% | DE  |

The hierarchical model of the neural network classifier of the functional state of the respiratory system, based on the descriptors obtained from the analysis of the Fourier spectrum of the wavelet coefficients of the ECS, surpasses the X-ray study in specificity and is somewhat inferior in sensitivity, which allows us to recommend the obtained classifier of the functional state of the respiratory system into clinical practice.

Acknowledgments
The reported study was funded by RFBR, project number 20-38-90058.

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