Technical science and innovation

Volume 2020 | Issue 4 Article 10

12-28-2020

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BIOMEDICAL ENGINEERING AND BIOENGINEERING

UDC: 004:616.(12)

A METHOD FOR CLASSIFYING ECG SIGNALS WITH DIFFERENT POSSIBLE STATES ON A MULTILAYER PERCEPTRON

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Annotation. *To automatically determine the state of the cardiovascular system based on the recorded ECG signals, an artificial neural network is trained to classify signals into various possible states. At the same time, the parameters of heart rate variability (HRV) were extracted from the ECG signals and used as input functions for the neural network. HRV is the fluctuation in the time intervals between adjacent heartbeats. For this, the architecture of a neural network based on a multilayer perceptron and a method for obtaining the necessary parameters in the learning process have been developed, and the classification efficiency has been checked and evaluated.*

Key words. *ECG, neural network, multilayer perceptron, heart rate variability, the autonomic nervous system of the heart.*

Introduction. Medical Information - The ECG signal functions, obtained after analyzing the ECG signal, are very important for determining the patient's physical condition, diagnosing cardiovascular disease, or determining medical treatment.

Digital time series analysis is used to quickly and reliably move from subjective to objective diagnosis and automatically detect serious cardiovascular disease. A wide range of methods for analyzing ECG signals have been investigated. One possibility is to use an artificial neural network with ECG signal functions extracted from the wanted signal as input to make an assumption about cardiovascular condition or potential cardiovascular disease as an output. A trained neural network can be used to classify ECG signals and thereby help diagnose the correct symptoms or diseases. Cardiac signals, or rather heart rate, can serve as an indicator of the adaptive responses of the nervous system.

In the cardiovascular system, the autonomic nervous system of the heart (ANS) is an essential component of physiological and pathological reactions. The ANS controls many events across two branches, the sympathetic and parasympathetic nervous systems (SNS and PNS), which take into account the corresponding blood pressure, heart rate, and vaso-regulatory responses to everyday stimuli.

Dysregulation of this system due to aging, acute and chronic stress and other causes contributes to the development of cardiovascular pathology, including hypertension, coronary heart disease, arrhythmias and congestive heart failure. For a qualitative description of the relationship between the sympathetic and parasympathetic parts of the nervous system and their influence on the function of the sinus node of the ECG, heart rate variability is used.

There is a wide range of HRV parameters that can either be calculated from time or frequency measurements, or can be linear or non-linear. Time domain indices indicate the amount of HRV observed during monitoring periods. Domain frequency values calculate the absolute or relative amount of signal energy in the frequency bands of the components. Non-linear measurements quantify the unpredictability and complexity of a series of beat intervals. HRV can be an indicator of short-term, long-term or general variability and, in addition, can be attributed to the activity of the sympathetic or parasympathetic nervous system, or both. However, a clear assignment for all HRV indicators is impossible. Since the interaction and balance of both SNS and PNS is complex and also varies in healthy patients due to the response to routine daily stimuli, it is difficult to diagnose cardiovascular disease by HRV parameters. A comparative analysis of several HRV parameters is recommended to study the patient's health status.

Method. Heart rate variability consists of changes in the time intervals between successive heartbeats, called the intervals between beats. To calculate these HRV parameters, you need to segment the filtered ECG signal into individual heartbeat periods and calculate the intervals between beats. Since the R-peak is the most recognizable characteristic in the ECG signal, it is used to identify and isolate periods from each other (Fig. 1). For this task, the segmentation algorithm presented by Engelse and Zeelenberg with modifications by Lourenco et al. Was used, as well as the R-peak correction function, which are part of the BioSSPy package. Given the R-peaks, the RR-intervals were calculated, from which information about the heart rate and associated symptoms can be obtained.

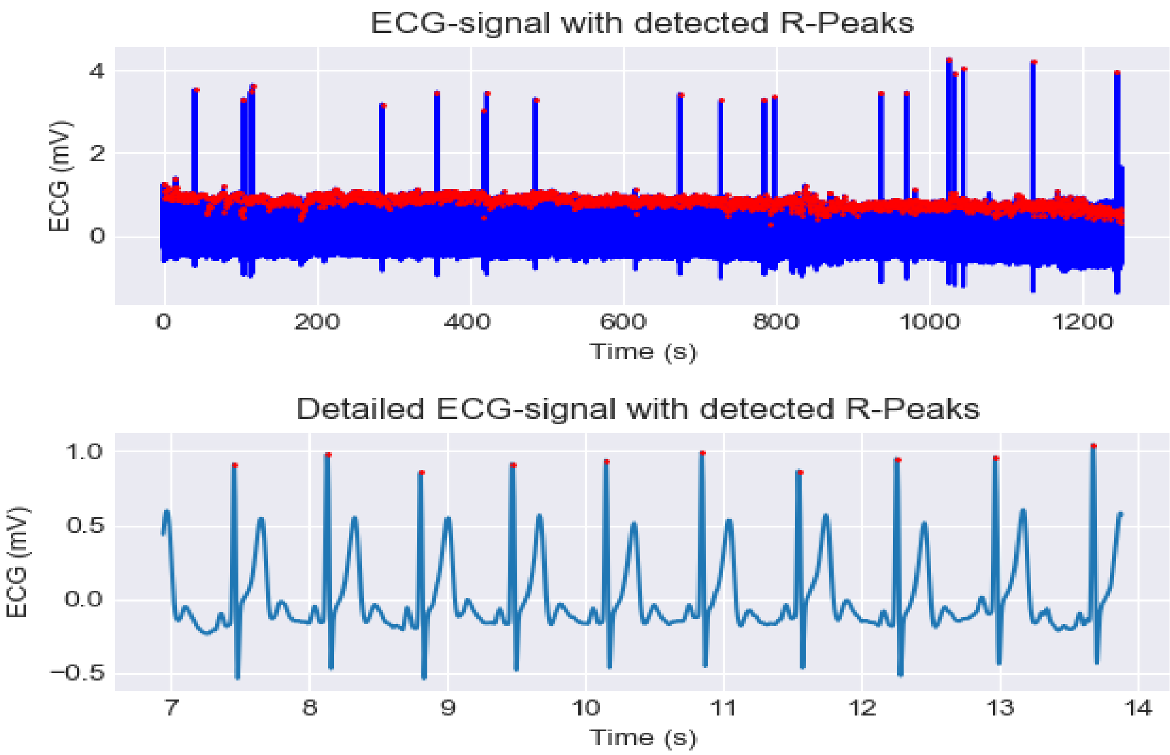

Fig: 1. R-peak detection

To reject outliers of RR intervals resulting from undetected or erroneously detected R peaks, which can distort the true information, filtering was performed to the so-called NN intervals (from normal to normal) (Fig. 2).

First, any interval less than 0.3 s or greater than 2.0 s is flagged as an outlier and is excluded from the series of intervals. The misaligned beats are then detected using Malik's rule that adjacent intervals should not differ by 20%.

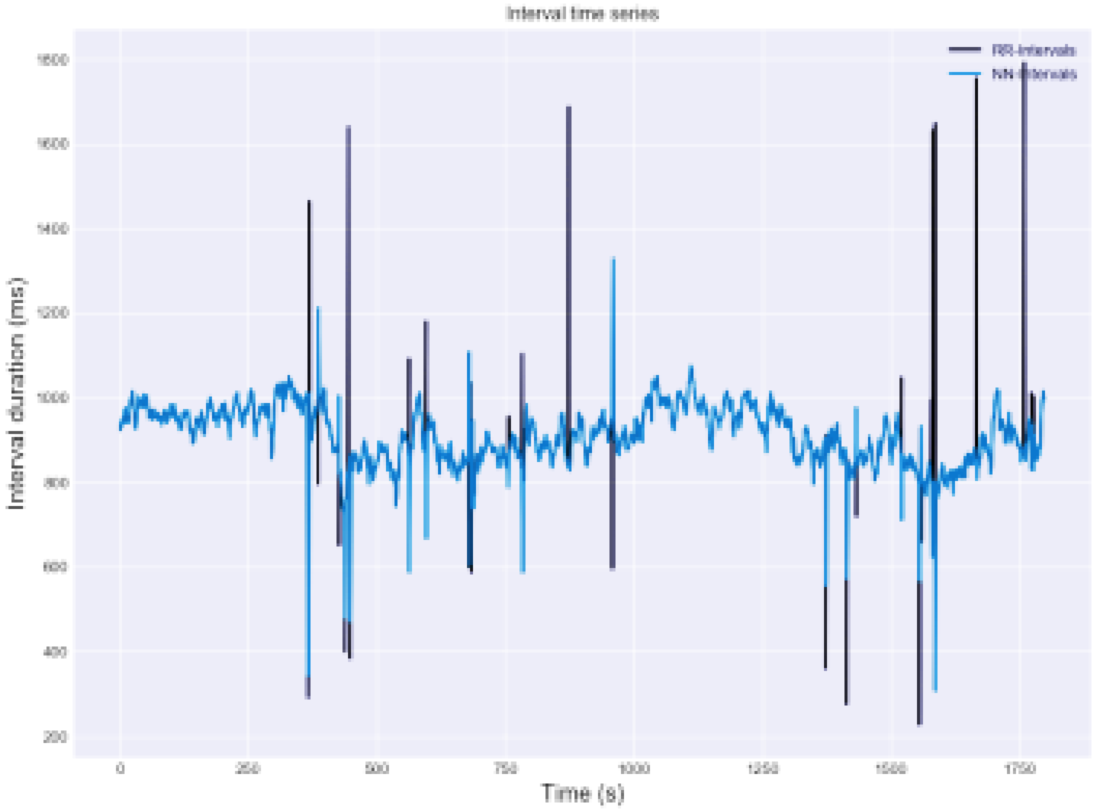

Fig: 2. Outliers and offset beats for calculating NN intervals for calculating HRV.

In the next step, these intervals are interpolated linearly. The intervals that could not be interpolated are excluded from the series. With this procedure, deviations due to insufficient R-peak detection can be prevented. Note that not all misaligned beats can be eliminated with this method, and as a result, there will still be displacement in the HRV calculation.

Heart rate variability parameters are a reasonable choice because they characterize a series of heartbeats and can be used as an indicator of cardiovascular health. For this we have selected twelve parameters of heart rate variability, which are listed in Table 1. Most of them are descriptive statistical parameters and can be calculated using the corresponding function of the statistics package. Some parameters are calculated by calculating the autocorrelation function, also provided by the statistics package.

Table 1

AVNN	Average value of NN intervals
SDNN	Standard deviation of NN intervals
RMSSD	Variation range of heart rate
SKEW	Asymmetry coefficient (asymmetry)

KURT	Excess ratio (kurtosis)
MO	Most probable value of NN-interval (Mode)
AMO	Mode amplitude
MO	The amount of shift at which the first negative value of the correlation coefficient appeared
R1	Correlation coefficient after the first shift
DELp	Number of positive corrections (analysis of subsequent NN intervals)
DELO	Number of zero patches
DELn	Number of negative corrections

To obtain medical information from ECG signals and calculated functions, it is necessary to develop a classification algorithm that takes the relevant characteristics (features) as input and predicts the most likely class from a predetermined set of classes. There are several methods for solving the classification problem, such as Bayesian classifier, decision trees, random forests, support vector machines, and artificial neural networks. The most effective of these is the artificial neural network training method. There are a wide range of different approaches within this teaching method, such as multilayer perceptrons (MLP), convolutional and Hopfield networks as supervised (supervised) teaching methods, and some unsupervised teaching methods. This paper explores the possibility of classifying ECG signals through a multilayer perceptron, since this is a truly effective approach for solving classification problems.

The idea of artificial neural networks, or rather a feed-forward neural network, is roughly derived from how the brain works: information enters a network of connected neurons as input, processed by passing through weighted connections, and generates output according to the input. The basis of the model underlying the network is called the perceptron, which consists of 4 parts: input values or one input layer, weights and biases, the resulting network and the activation function (Fig. 3). The perceptron's workflow covers specific steps, starting with multiplying all inputs X by their weights W, adding all the multiplied values to a so-called weighted sum, and applying that weighted sum to a specified activation function that determines the perceptron's output. In relation to a multilayer perceptron, it consists of an input layer with neurons equal to the number of input feature vectors, an output layer with neurons equal to the number of predictable classes, and a certain number of hidden layers (at least one) with a (arbitrary) specified number of neurons.

A supervised learning approach is commonly used to train a network of classifiers, which means that there is a labeled dataset that provides the correct class for each sample. The labeled dataset is divided into a training dataset, which trains the network to obtain the actual classification of the data, and a test dataset to evaluate the network's performance. In addition, the training dataset itself is subdivided into the actual training dataset and the validation dataset, which measure performance during the training process, since it is important to test the performance of the network with brand new data. This is done by cross-checking, i.e. multiple runs with different training or validation subsets are used to minimize the stochastic effects of randomly assigning subsets.

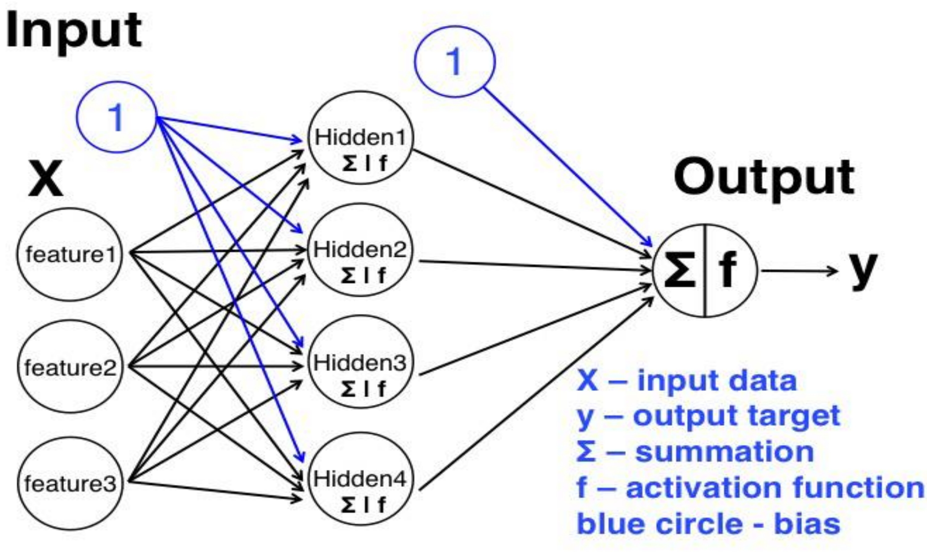

Fig. 3. Multilayer perceptron neural network architecture.

All datasets are sliced by delamination, which means that each class in the dataset is represented according to its frequency in the original dataset to eliminate the possibility of insufficient samples of one class during the training or testing process. The training requires a backpropagation step that adapts the weights and biases to reduce the error resulting from the difference between true and predicted labels.

There are three main algorithms for performing weight optimization: the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (an optimizer in the family of quasi Newtonian methods), stochastic gradient descent (SGS), and adam, a solver that refers to a stochastic gradient optimizer proposed by Kingma, Diederik, and Jimmy Ba. For small datasets, it is preferable to use the BFGS and CGS solver as they converge faster and perform better. By default, precision (percentage of correctly predicted samples) is used as a measure of error. However, this estimate has certain drawbacks as it reflects overall accuracy and does not take class distribution into account. Therefore, the best approach is to compute a weighted F estimate or area under the receiver-operator curve. In this case, you can get an accurate estimate of the percentage of correctly predicted positive samples from the samples and determine the percentage of correctly predicted positive samples from the positive class to increase efficiency. Next, a weighted F-score is used, which in its basic form can be calculated by the formula

$$F1 = 2 * \frac{\text{accuracy} * \text{choice}}{\text{precision} + \text{choice}}$$

When designing a neural network architecture, that is, the number and size of hidden layers is very important for the efficient organization of the neural network (Figure 3.19). It can be pointed out that for most classification problems it is sufficient to have only one hidden layer, so the focus is on organizing the structure based on the number of neurons in one hidden layer. Another important factor is the selection of the activation function. Commonly used activation functions are the logistic sigmoidal function f (x) = 1 / (1 + exp (-x)), the hyperbolic function f

(x) = tanh (x), and the rectified linear unit function f (x) = max (0 , x). The ANN training algorithm is shown in Figure 4.

There are several preprocessing steps for the input vector that can be performed to increase the efficiency of the neural network. First, the input values are scaled, since the range of the input values has a direct effect on the weighted sum and result of the activation function, and therefore it is preferable that all functions remain in the same range. Possible scaling tools are StandardScaler, which keeps the average of the training samples at 0 and variance at 1, and MinMaxScaler, which scales the samples in the range (0.1).

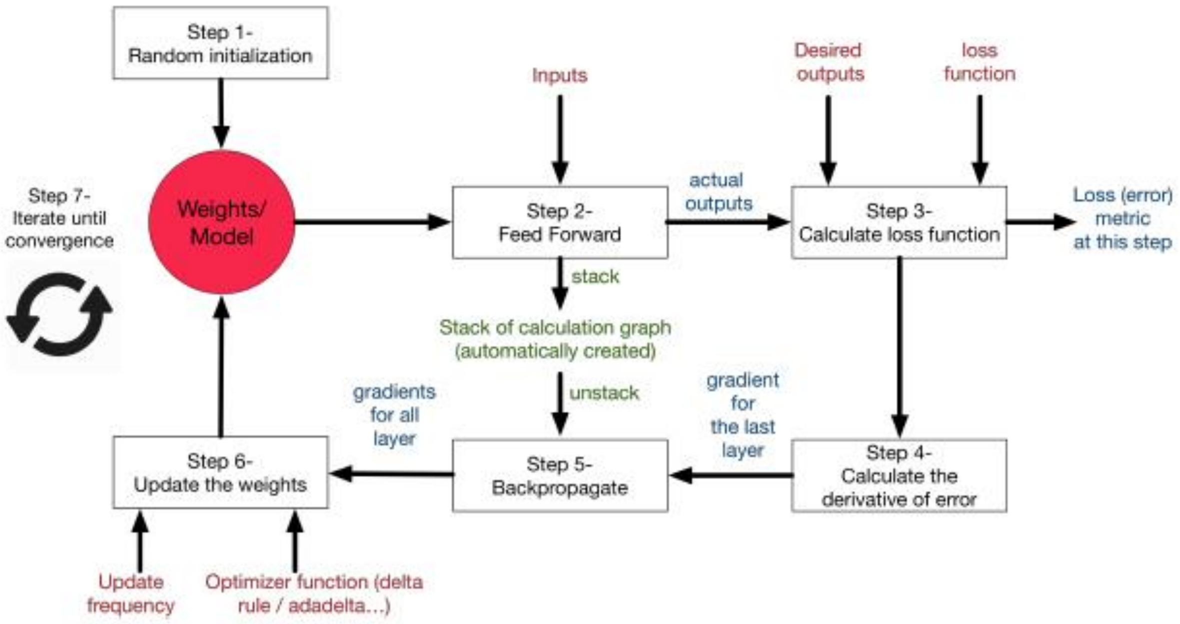

Fig. 4. Algorithm for learning an artificial neural network.

An effective method for reducing the size, as well as extracting the informative parts of the input vector, is the principal component analysis (AOC) method. This method reduces the size of the input vector to a specified number of principal components that maximize the necessary information stored in the input vector.

As mentioned above, creating a multilayer perceptron classifier requires a labeled dataset to learn the classification rules. For this, two sets of data containing ECG signals were provided and combined. One is the MIT-BIH Arrhythmia Database, which contains 48 half-hour copies of ECG recordings from 47 patients at Boston Beth Israel Hospital. The second is the ROHMINE database containing 70 half-hour records published by the Russian Society for Holter Monitoring and Non-invasive Electrophysiology. However, in both cases, labeling datasets is quite difficult.

First, it is necessary to define categories, the so-called classes, that describe the various states of the ANN. The state can be either balanced, so that the regulation of both the sympathetic and parasympathetic nervous systems is working normally, or unbalanced, which can mean any dysregulation of the interacting system. Here, the unbalanced state is divided into two classes, which indicates an increased activity of the SNS and PNS, respectively. In this case, there may be more possible classes, for example, different levels of hyperactivity, both SNS and PNS, or insufficient function of one of the branches of the nervous system. For simplicity, the number of classes is limited to the three classes shown.

Second, an appropriate indicator is needed to assign samples to one of the three classes.

In this case, the HRV parameter of the ratio of the LF to HF power (LF / HF ratio) is used, which can assess the relationship between the activity of the sympathetic nervous system and the parasympathetic nervous system. Let's say the underlying LF / HF ratios are that LF power (power density in the low frequency range 0.04-0.15 Hz) can be generated by the SNS, while HF power (power density in the higher range frequencies 0.15-0.40 Hz) will be generated by the PNS. In this model, a low LF / HF ratio reflects parasympathetic dominance, and a high LF / HF ratio indicates sympathetic dominance. Specific values for the normal range of the LF / HF ratio are obtained from studies by Kim et al. The 25th and 75th percent values of the LF / HF ratios were used as the lower and upper thresholds for classifying the samples, respectively. So, the division into classes was carried out according to the following decision-making rules. Decision rules for class assignment are shown in Table 2.

Table 2

Class	Description	Range
0	Balanced состояние	0.9 <= LF / HF range <= 3.1
1	Overactive PNS	LF / HF range <0.9
2	excessive SNS activity	LF / HF range> 3.1

Findings.. The analysis of detection of R-peaks and calculation of RR-intervals, as well as heart rate, taking into account the parameters of heart rate variability, was carried out. The choice of hyperparameters and parameters of the time and frequency domains of heart rate variability as input functions of the neural network has been substantiated. ... Calculations of the parameters of heart rate variability, which characterize a series of periods of heart contractions, are given and are used as an indicator of the state of the cardiovascular system.

Conclusion. Algorithms of a neural network for learning vector quantization and a multilayer perceptron have been developed to classify ECG signals taking into account various possible ECG states and cardiac abnormalities - normal, bradycardia, tachycardia, PSG and myocardial infarction, and the efficiency of the preferred neural network model with extended functions has been calculated.

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