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Intelligent Classifier Based on Radial Basis Function Network for the Task of Identification the Recurrent Laryngeal Nerve in a Surgical Wound

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Abstract. *The application of radial basis function networks (RBFN) for identification the recurrent laryngeal nerve (RLN) in a surgical wound was proved in this paper. The intelligent classifier based on artificial neural network with radial basis functions (RBF) was created. The task of identification the recurrent laryngeal nerve during thyroid surgery in the process of classification the information signals from different patients is considered.*
Keywords: *intelligent classifier, artificial neural networks, radial basis function network, recurrent laryngeal nerve, identification.*

1. Introduction

During the thyroid surgery there is the task of RLN identification. RLN damage leads to negative consequences (loss of voice). Modern devices for RLN detection are based on stimulation the surgical area by alternating current with fixed frequency and the evaluation the results of stimulation on the vocal cords [1].

Information signal as the result of stimulation the surgical area characterizes whether the point of stimulation belongs to RLN or muscle tissue. Nowadays there isn't unified methodology for detailed research the parameters of resulting information signal (RIS) and their classification. Though the high sensitive devices were used the results of information signal analysis often leads to mistakes in decisions of a surgeon. Thus the task of classification the received information signals to reduce the risk of RLN damage is actual.

In the paper [2], the method of RLN identification in the surgical wound by an RIS amplitude is considered. However, the amplitude of the information signal is so high during the laryngeal nerve stimulation and decreases sharply (to noise level), when moved from it even slightly. It essentially reduces the possibility of visualization the location of laryngeal nerve during the thyroid surgery.

Other approaches to RIS analysis are based on an analysis of its spectral characteristics [3]. It's known that during RLN stimulation there is a contraction of muscles that stretch the vocal cords. Thus it is assumed that during muscle tissue stimulation the signal spectrum is one and during the nerve stimulation is another.

The RIS is a sound signal that occurs during inhalation and exhalation of the air by a patient and is modulated by the contraction of vocal cords. Therefore, RLN identification during thyroid surgery by the signal spectrum is significantly complicated by the peculiarities of each patient's larynx.

From the foregoing follows the advisability of using the new mathematical methods, including classification methods, to analyze the RIS from different patients. These new methods will allow to increase the accuracy of identification and reduce the risk of RLN damage in the surgical wound.

2. Proving the choice of method and tools for classification

There are many classification methods, in particular which based on method of the nearest neighbor or method of support vector or statistical methods [4]. However, these methods have significant limitations:

- require large data sets;
- use complicated computational procedures;
- have low classification accuracy.

Among all classification methods it is necessary to consider the neural network approach which is described by [4, 5, 6]. An important feature of any neural network is the ability to learn, which is to determine such ANN parameters in which the network produce the necessary output signals. The previous research [7] showed that among all known artificial neural networks the radial basis function networks differ positively by offering simple architecture (one hidden layer) and high-speed learning. With this in mind, as a model for the RIS classification in the task of RLN identification an RBFN should be used.

The output signal from RBFN is set by the equation:

$$y_j = \sum_{i=1}^{h} w_{i,j} f_i(\|\vec{x} - \vec{c}_i\| \sigma^{-2}), \tag{1}$$

where y_j is j output signal of neural network ($j = 1, 2, \ldots, m$, where m is number of outputs); w_{ij} are weighting coefficients of synaptic connections; $\{f_i(\|\vec{x} - \vec{c}_i\|)\}$ is a set of h RBF; $\|\cdot\|$ is an Euclidean norm; $\vec{x}$ is a vector of inputs; $\vec{c}_i$ is a centers of RBF; h is a number of hidden layer neurons in the network.

Thus, the aim of this paper is to analyze the RIS characteristics and to detect the RLN among other tissues in surgical wound using the classification based on RBFN.

3. General block diagram of a classifier based on RBFN

General block diagram of a intelligent classifier is shown in Figure 1. Operating features of intelligent classifier are given below. The RIS obtained after stimulation the tissues in a surgical wound of some patient is sending to the classifier input. Block of information signals preprocessing (BISP) is destined to increase the informative content of the signal, that is considering the presence the qualitative characteristic and the noise in signal, it is necessary to increase the RIS to noise ratio. Parameters characterizing the information signal that received in BISP are sending further to the input of block of decision making (BDM). In this block after analysis the set of parameters of the information signal it is makes the decision whether the point of stimulation belongs to nerve or muscle tissue. At the output of intelligent classifier is the result of classification. Block of decision making is based on RBFN.

As can be seen from the diagram shown in Figure 1, to each of the two classes corresponds the one specific output for one-valued recognition the input data by classes.

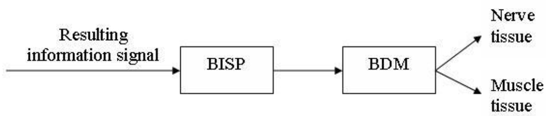

Figure 1. General block diagram of intelligent classifier

4. Proving the choice of informative parameters of the information signal

In detail the scheme for obtaining the RIS for RLN identification from other tissues in the surgical wound is described in the paper [8]. An example of the RIS of some patient is shown in Figure 2.

From the results of a RIS research it was determine that the first two parts of RIS $u(t)$ shown in Figure 2 are the result of reaction to stimulation the muscle tissue, and the next two are the RLN.

In the paper [9] it was determined that parts of the information signal $u(t)$ which correspond with reaction to the RLN stimulation, have a similar structure (view) to the autocorrelation function and significantly differ from the kind of autocorrelation function corresponding with muscle tissue stimulation. Given this the autocorrelation characteristics of RIS fragments was used to RLN identification in the surgical wound with RBFN application. In Figures 3 and 4, as an example, there are shown the graphs of the autocorrelation functions of the information signal. They characterize the reaction to stimulation the muscle tissue and the laryngeal nerve, respectively.

For RIS classification as feature vectors it was chosen the signal energy spectrum obtained by the fast Fourier transformation (FFT) of the autocorrelation function. In Figures 5 and 6 the energy spectrum of RIS fragments corresponding to the muscle and the nerve tissue respectively are shown.

After analyzing the experimental results, it was found that the energy of information signal as response to the muscle tissue stimulation is concentrated in much lower frequencies (8.82 - 22.05 Hz) than the energy of the signal as response to RLN stimulation. It is an essential informative feature of RIS.

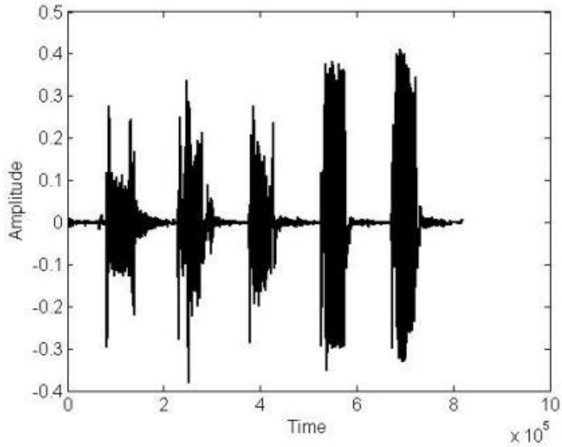

Figure 2. RIS obtained during stimulation the tissues in a surgical wound

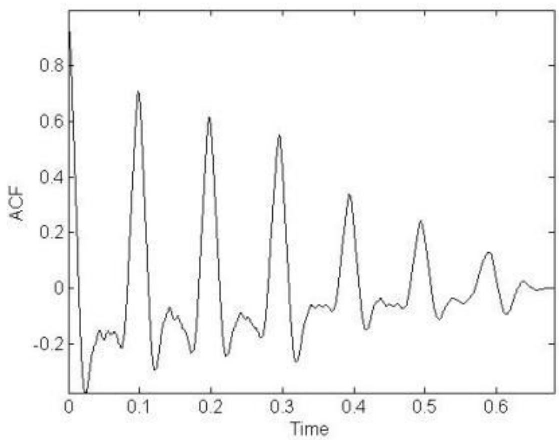

Figure 3. The autocorrelation function of the information signal $u(t)$ as response to stimulation the muscle tissue

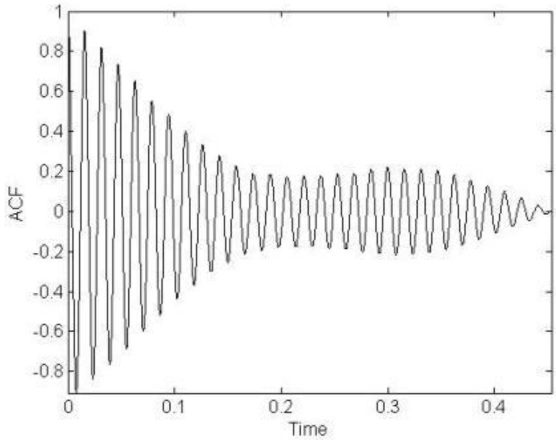

Figure 4. The autocorrelation function of the information signal $u(t)$ as response to RLN stimulation.

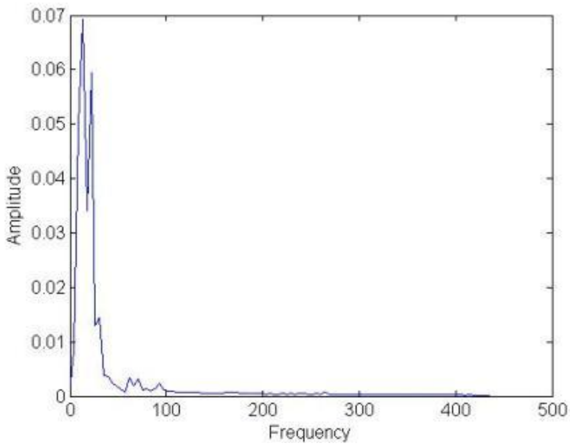

Figure 5. The energy spectrum of signal as response to the muscle tissue stimulation

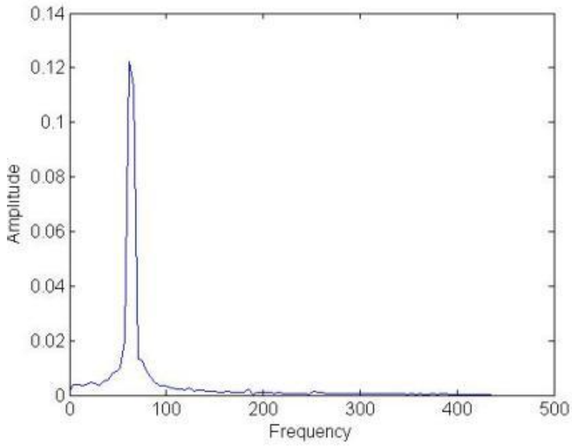

Figure 6. The energy spectrum of signal as response to RLN stimulation

5. An example of RLN identification during thyroid surgery with RBFN application

The information signals were research for different patients. The RBFN was applied as a model for the RIS classification. Since the energy spectrum of the signal was obtained using FFT, then the size of FFT block is F_b=512 and the information signal is represented by N_h=0.5, F_b=256 counts.

For RBFN training it was created a database with spectral characteristics (amplitude and frequency) of desired information signals. The vector containing spectral characteristics of RIS counts was sent to the RBFN inputs. The number of neurons in the input layer is corresponding to the number of counts N_h. Hidden layer of RBFN contains the 2 neurons because the classification task has 2 classes. Only one output signal is received in the output of neural network. It characterizes the information signal belonging to one from two classes: the RLN or the muscle tissue. For RLN identification in the surgical wound it was used the following code: 1 is the RLN and 0 is the muscle tissue. RBFN was based on the known feedback error learning algorithm. According to this algorithm the task of finding such weighting coefficients w_i is solved at which the minimum of the sum of squares for error (SSE) is reached.

The RBFN structure 256:2:1 for RLN identification from other tissues in the surgical wounds is shown in Figure 7. For the RBFN testing it was send a signal that is not present in the training data set to the RBFN inputs. To implement the algorithm for RLN identification in the surgical wound it was used the Matlab 7.1. The result of RIS classification for RLN identification of some patient is shown in Figure 8.

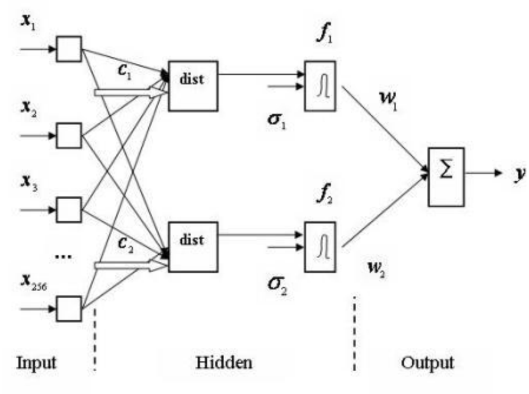

Figure 7. The RBFN structure for RLN identification in the surgical wound

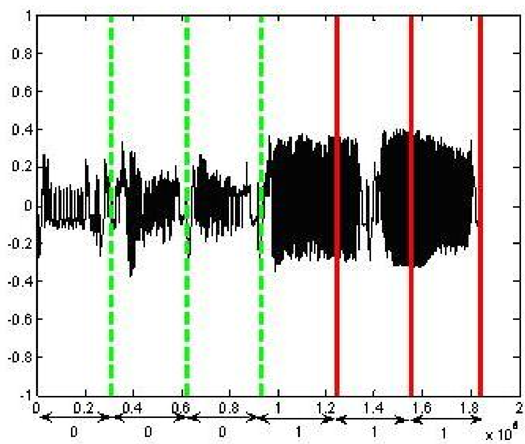

Figure 8. RIS classification with the RBFN using

The dashed line indicates a fragment of signal as reaction to the muscle tissue stimulation and the solid line is a fragment of information signal as reaction to RLN stimulation. The result of RIS classification with the RBFN using by classes coding is displayed as follows: 0 0 0 1 1 1. The classification of the 150 information signals from different patients was conducted during the research. 11 from them were false classified, therefore the accuracy of classification is 92,7%.

The results of classification demonstrate the perspective of RBFN using for RLN identification in the surgical wound by the RIS analyzing (their autocorrelation characteristics).

6. Conclusions

The task of RLN identification in the surgical wound using the RIS classification on the basis of RBFN was considered. In the process of noted task solving the following scientific and practical results were obtained.

1. The general block diagram of classifier for classification the responses as reaction to stimulation the tissues in surgical wound was proposed and proved. This diagram unlike existing ones includes the block of decision making based on RBFN.

2. The parameters of the information signal as reaction to stimulation the tissues in the surgical wound that provide identification the tissue type in the stimulation point was proved. It was found that these parameters are the spectrum of autocorrelation function of RIS.

3. The structure of RBFN for solving the task of RLN identification during thyroid surgery is proposed and proved. The efficiency of this classifier was confirmed on the data set including 150 information signals from different patients. It is shown that the classification accuracy with RBFN using for a given data set of information signals is 92.6%.

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