Artificial neural networks and wavelet analysis in bio-radiolocation signal breathing patterns classification

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***Abstract* — A new approach for bio-radiolocation signal breathing patterns classification, based on artificial neural networks and wavelet analysis technique utilization, was proposed. Patterns attribute space is formed utilizing series of absolute values of wavelet decomposition detail coefficients of signal quadrature components. A multilayer perceptron with a backpropogation training algorithm and a bipolar sigmoid activation function of neurons was applied as a classifier. Analysis of efficiency of the method, carried out on bio-radiolocation signal models, revealed high classification accuracy on test sample of breathing patterns corresponding to three different classes: obstructive sleep apnea, central sleep apnea and normal calm sleeping.**

Keywords: bio-radiolocation, artificial neural network, wavelet analysis, breathing pattern, apnea syndrome.

I. Introduction

Early recognition and proper classification of apnea episodes are both very important stages in treatment strategy planning and opportune preventive measures taking [1]. Application of artificial neural networks is considered to be an effective instrument in the tasks of classification of breathing patterns, recorded from abdominal and thoracic belt perimetric sensors [2]. Multiresolution wavelet analysis is a perspective mathematical apparatus which is extremely needed in processing of non-stationery multicomponent signals with noise, which have high-frequency components of short duration and prolonged low-frequency components [3]. Based on two mentioned approaches, a new method of bio-radiolocation signal breathing patterns classification was developed.

II. Materials and methods

A. Bio-radiolocation technology

Bio-radiolocation is a modern sensing technique giving the opportunity to detect persons remotely even behind opaque obstacles, not applying any contact sensors [4]. It is based on radar signal modulation by oscillatory movements of human limbs and organs. Electromagnetic wave reflected from human body obtains specific biometric modulation which is not present when interacting with motionless objects [5]. The main factors of such signal changes are: heartbeat; contractions of vessels; movements of limbs; oscillation processes of cutaneous integument of chest wall and abdomen areas.

B. Attribute space forming

Using wavelets, received radar signal can be represented as a set of functions, formed by the base one. The number of wavelets applied defines the decomposition level of the signal. The accuracy of signal representation is lessened, when increasing the decomposition level. But in this case the lower frequency components of the signal fraction can be examined in more details. Wavelet coefficients describing low frequency components of the signal interval of interest give the opportunity to classify and discern objects in received radar signal even with rather high level of noise [6].

The vector of absolute values of detail coefficients, representing low frequency components of both received signal quadratures, was chosen as an attribute one. Thereby each component of the attribute representation vector on the chosen operational frequency at each decomposition level can be calculated as [7]:

$$V_j = \sqrt{\left(d_j^Q\right)^2 + \left(d_j^I\right)^2}\ , \tag{1}$$

j – the number of the component;

d_j^Q – detail coefficient of Q signal quadrature;

d_j^I – detail coefficient of I signal quadrature;

V_j – the attribute vector component.

According to [7] Haar wavelet was chosen a base one. Detail coefficients values were calculated using discrete wavelet transform procedure, implemented in MATLAB software.

C. *Neural network classifier organization*

For bio-radiolocation breathing patterns classification a multilayer perceptron [8] with a backpropogation training algorithm, one hidden layer and a bipolar sigmoid activation function of neurons was applied as a classifier.

Structure of neural network, shown in Fig. 1, consists of following elements:

$x_1, x_2, \ldots, x_N$ – input layer;

$g_1, g_2, \ldots, g_L$ – hidden neuron layer;

$y_1, y_2, \ldots, y_M$ – output layer;

w_{ij} – weight coefficients;

N – number of inputs;

L – number of hidden neurons;

M – number of outputs

The training characteristics of neural network used in this study are as follows:

- one input layer (16 inputs);
- one hidden layer (15 neurons);
- one output layer (3 neurons);
- activation function: bipolar sigmoid;
- training algorithm: backpropogation;
- adaptive learning coefficient: $\eta = 0.05$;
- sum-squared error limit: $SSE = 0.02$.

During performance analysis of the neural network, cross-validation was used for determining the final training moment to avoid overtraining. The aim of such stop criteria is to maximize the network's generalization capability [9].

To organize and perform the multilayer perceptron for bio-radiolocation breathing patterns classification Neural Network Toolbox was used which is implemented in MATLAB software.

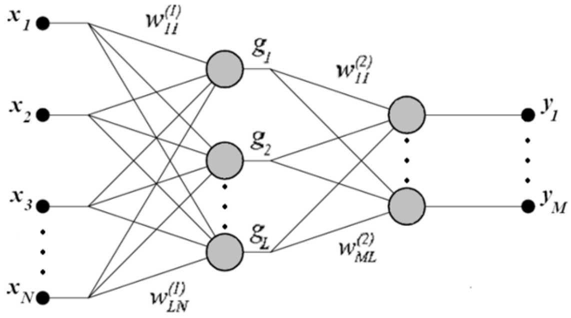

Figure 1. Structural scheme of neural network classifier

III. Experimentation

A. *Obtaining bio-radiolocation signal patterns*

Radiolocation information about target object can be received with the help of phase detection method. It affords to discriminate signals reflected from moving structures against background interactions with motionless objects [10]. According to the method of restoration of mechanical trajectory, knowing radar signal for point target performing reciprocal movements the following relation is known [11]:

$$\begin{cases} I(t) = I_0(t)\cdot\cos\left[4\cdot\pi\cdot f_0\cdot(\dfrac{R_0+R(t)}{c})\right] \\ Q(t) = Q_0(t)\cdot\sin\left[4\cdot\pi\cdot f_0\cdot(\dfrac{R_0+R(t)}{c})\right] \end{cases} \tag{2}$$

$I(t), Q(t)$ – recieved radar signal quadratures;

$I_0(t), Q_0(t)$ – amplitude values of quadratures;

$R(t)$ – reciprocal trajectory movement function;

R_0 – initial distance to target from antenna;

f_0 – frequency of radar probing signal;

c – electromagnetic wave propogation speed.

As it was shown in the study comparing data obtaining from remote bio-radiolocation method and contact abdomen belt sensor [12], satisfying agreement of the signal model and experimental results is reached when amplitude values of recieved quadratures are considered to be constant. Thereby, obtaining source data from belt abdominal sensor and accepting the assumption of uniform changing of perimeter into time, it becomes possible to model bio-radiolocation signal for different types of breathing patterns.

To get source data for the study, verified by experts signal fragments from belt perimetric abdominal sensors were used, obtained from MIT-BIH Polysomnographic Database [13]. All in all, 240 breathing patterns corresponding to three classes (obstructive sleep apnea (OSA); central sleep apnea (CSA); normal calm sleeping (NCS)) were analyzed in the study. Character signal shapes are given in Fig. 2.

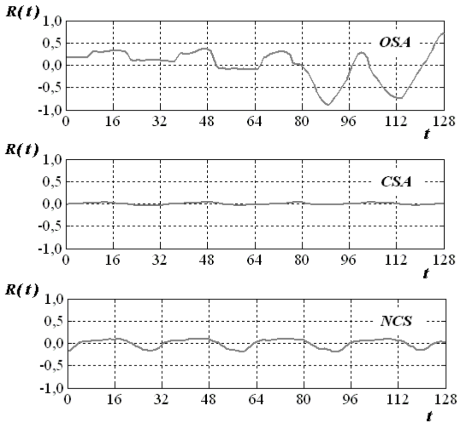

Figure 2. Breathing patterns character signal shapes corresponding to target classes

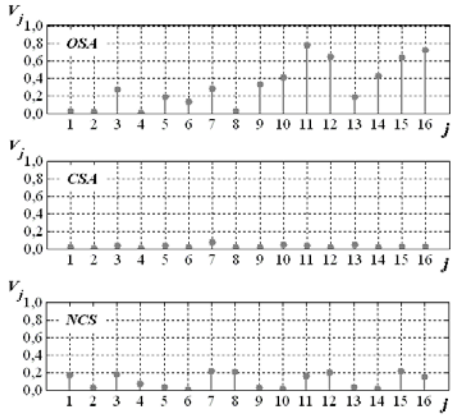

Figure 4. Character components values of attribute vectors corresponding to target classes

B. Data processing

The proposed method of bio-radiolocation breathing patterns classification consists of three main stages, which are given in Fig. 3. Before classifying breathing patterns preprocessing was carried out. For source data from perimetric abdominal belt sensors recorded with sampling frequency of 250 Hz the following main steps were consequentially performed:

- downsampling to 10 Hz;
- marking signals to fragments of 128 counts;
- forming a set of 240 verified breathing patterns;
- filtration with moving average filter;
- removing constant signal value;
- turning to bio-radiolocaton signal quadratures.

Then for bio-radiolocation signal components wavelet decomposition on the third level applying Haar wavelet was performed which provided 16 detail coefficients for each quadrature. Afterwards attribute space forming for bio-radiolocation signal breathing patterns was performed. So during data preprocessing stage for the three classes of breathing patterns attribute vectors with the fixed number of components were formed, which structures are given in Fig 4.

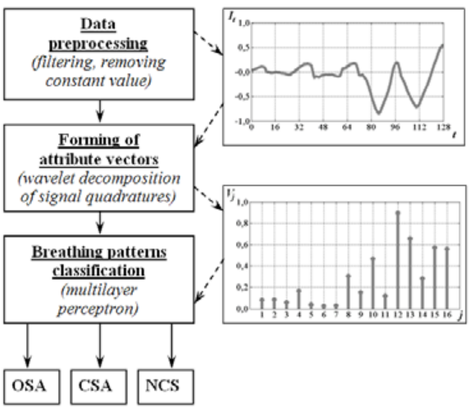

Figure 3. Structural scheme of proposed method of bio-radiolocation signal breathing patterns classification

The data consisting of 240 attribute vectors of bio-radiolocation signal breathing patterns was divided into training, validation and test sets in the way that the total number patterns in each target class (obstructive sleep apnea (OSA); central sleep apnea (CSA); normal calm sleeping (NCS)) was the same:

- 90 patterns (30 in each class) – training set;
- 30 patterns (10 in each class) – validation set;
- 120 patterns (40 in each class) – test set;

The suggested scheme of bio-radiolocation signal breathing patterns classification consists of three main parts. At first data preprocessing step for each signal quadrature fragment moving average filtering was performed and all the constant components were deleted. Then for selected breathing patterns attribute space was formed, based on utilization of series of absolute values of the third level wavelet decomposition detail coefficients of signal quadratures. A multilayer perceptron with a backpropogation training algorithm, one hidden layer and a bipolar sigmoid activation function of neurons was applied as a classifier. So every time applying the fixed number of 16 resulting components of attribute vectors to the inputs of the neural network as an output comes a value of one of the 3 target classes of bio-radiolocation breathing signal patterns.

C. Results

The trained neural network classifier was tested on a set of 120 bio-radiolocation breathing patterns, corresponding to 3 target classes. The classification efficiency is shown in Table I.

TABLE I. CLASSIFICATION EFFICIENCY OF BREATHING PATTERNS CORRESPONDING TO TARGET CLASSES

True	***OSA***	***CSA***	***NCS***	***β err.***
OSA	**38**	0	2	5,0%
CSA	1	**37**	1	5,1%
NCS	3	2	**36**	12,2%
α err.	9,5%	5,2%	7,7%	**92,5%**

The total accuracy of the proposed method performed on the test set turned out to be 92.5%. The average accuracies of classification for each type of bio-radiolocation signal breathing patterns came to the following values:

• 95.0% (β_{err} = 5.0%) – for obstructive sleep apnea;

• 92.5% (β_{err} = 5.1%) – for central sleep apnea;

• 90.0% (β_{err} = 12.2%) – for normal calm sleeping;

The analysis of errors of classification showed that for OSA and CSA episodes the type II error value did not exceed β_{err} = 5.1%. The most number of wrong classified objects corresponding to to NCS patterns came to the value of β_{err} = 12.2%. The type I error for OSA and CSA episodes did not exceed the value of α_{err} = 9.5%. Thus the proposed method of bio-radiolocation breathing patterns classification should be considered as an effective one and its accuracy satisfies standard recommendations on sleep apnea syndrome diagnostics [14].

IV. Conclusion

A new method of bio-radiolocation signal breathing patterns classification was developed based on application of artificial neural networks and wavelet analysis techniques. An attribute space of patterns was formed on the base of absolute values of wavelet decomposition detail coefficients of received radar signal quadratures . A multilayer perceptron with a backpropogation training algorithm, one hidden layer and a bipolar sigmoid activation function of neurons was used as a classifier. During experimental study a set of 240 modeled breathing patterns of bio-radiolocation signal was analyzed corresponding to the three target classes: obstructive sleep apnea, central sleep apnea and normal calm sleeping episodes. The total accuracy of classification came to the value of 95.2%. The obtained results satisfy standard recommendations on sleep apnea syndrome diagnostics. For further research in this field analysis of the efficiency of the proposed method depending on organizational structure of neural network classifier and the type of training algorithm should be made.

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