Selection of Wavelet Transform and Neural Network Parameters for Classification of Breathing Patterns of Bio-radiolocation Signals

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Abstract. A novel method for classification of breathing patterns of bio-radiolocation signals breathing patterns (BSBP) in the task of non-contact screening of sleep apnea syndrome (SAS) is proposed, implemented on the base of wavelet transform (WT) and neural network (NNW) application with automated selection of their optimal parameters. The effectiveness of the proposed approach is tested on clinically verified database of BRL signals corresponding to the three classes of breathing patterns: obstructive sleep apnea (OSA); central sleep apnea (CSA); normal calm sleeping (NCS) without sleep- disordered breathing (SDB) episodes.

Keywords: bio-radiolocation, non-stationary signal processing, pattern recognition, wavelet transform, neural networks, sleep apnea syndrome.

1 Introduction

One of the priority areas of sleep medicine is implementation of novel technical approaches for remote vital signs monitoring [1], particularly in screening of sleep disordered breathing (SDB), which is character for sleep apnea syndrome (SAS) [2]. Early detection and proper classification of SDB episodes is an important aspect of SAS treatment strategy planning and taking of opportune preventive measures in clinical practice [2].

Bio-radiolocation (BRL) is a modern remote sensing technique allowing to perform non-contact vital signs monitoring of living objects, on the base of analysis of specific biometric modulation in reflected radiolocation signal [1]. Previously reliability and correctness of BRL technology application for non-contact breathing monitoring [3] and remote screening of SDB [4] was successfully demonstrated.

T.D. Pham et al. (Eds.): ACBIT 2013, CCIS 404, pp. 175–178, 2014.

The aim of this study is development of a novel method for classification of breathing patterns of bio-radiolocation signals (BPBS) in the task of non-contact screening of SAS with automated selection of optimal parameters of wavelet transform (WT) and artificial neural network (NNW). The proposed approach is tested in classification of clinically verified BPBS corresponding to the following classes: obstructive sleep apnea (OSA); central sleep apnea (CSA); normal calm sleeping (NCS) without SDB.

2 Optimization Criterions

2.1 Criterion of the Optimal Level of Wavelet Decomposition

Suppose to be known the upper limit f_{m} of frequency band in which the most of energy of an analyzed signal is concentrated and the maximum possible frequency of its registration which comes to a half of sampling the frequency f_{S} value in accordance with Nyquist theorem. Then the optimal decomposition level (ODL) of WT for an analyzed BRL signal can be calculated from the relation [5]:

$$L_{\mathrm{O}} = \left[\log_2\left(\frac{f_{\mathrm{S}}}{2 \cdot f_{\mathrm{m}}}\right)\right] + 1 = -\left[\log_2\left(2 f_{\mathrm{m}} \Delta t\right)\right] + 1 \tag{1}$$

where f_{m} — the upper limit of frequency band in which the most of signal energy is concentrated; f_{S} — sampling rate; Δt — sampling period.

Thus, further decomposition of analyzed signal to the levels exceeding the threshold of ODL is not effective. Newly calculated detailed coefficients of WT are supposed to be not informative in the aspect of effective feature extraction for BPBS attribute space constructing.

2.2 Criterion of the Optimal Basis of Wavelet Transform

For selection of the optimal basis of WT from the class of orthogonal wavelets with compact support a modified entropy based criterion (MEC) is proposed which is calculated on the base of logarithm energy entropy estimation in the task of classification of BPBS:

$$E_{\mathrm{O}} = -\sqrt{\frac{1}{CN}\left(\sum_{k=1}^{C}\left(\sum_{i=1}^{N}\left(\sum_{j=1}^{K}\ln\left(\sqrt{(d_j^Q)^2 + (d_j^I)^2}\right)\right)\right)\right)} \to \min \tag{2}$$

where E_{O} — estimate of MEC; C — number of classes of patterns; N — number of patterns in each class; K — number of resulting components in attribute vectors; d_j^Q — detailed wavelet coefficient for Q-quadrature of BRL signal; d_j^I — detailed wavelet coefficient for I-quadrature of BRL signal.

Selection of the optimal basis of WT for effective BPBS attribute space forming should be performed using mean squared values of detailed wavelet coefficients of each BRL signal quadrature for MEC calculations.

2.3 Criterion of the Optimal Number of Hidden Neurons

For selection of the optimal number of hidden neurons of MLP applying WT and NNW for BPBS recognition the mean classification accuracy (MCA) criterion is proposed which is based on classification accuracy values estimation at each analyzed wavelet basis. Varying in each operation test the number of hidden neurons of NNW the estimate of A_0 is calculated as follows:

$$A_O = \frac{1}{MB}\left(\sum_{m=1}^{M}\left(\sum_{b=1}^{B} C_b\right)\right) \to \max \tag{3}$$

where A_O — estimate of MCA; M — number of operation tests; B — number of analyzed wavelet basis; C_b — recognition accuracy for analyzed wavelet basis.

Selection of the optimal number of hidden neurons of MLP with application of MCA criterion should be performed using wavelet basises with such ordinal indexes for which the minimal values of MEC are achieved on training data set.

3 Structure of the Optimization Algorithm

The proposed algorithm for automated selection of optimal parameters of WT and NNW for improving of the performance of BPBS classification consists of the two main stages. In the first stage, for informative feature extraction applying WT, initially a general class of wavelets is defined, then a set of wavelet basises with ordinal indexes for wavelet families from the general class is formed, afterwards the optimal level of wavelet decomposition is determined, finally the optimal wavelet basis is selected on the base of MEC. In the second stage, for improving NNW operation performance, after preliminary estimation of number of hidden such their optimal amount is found for which the best MCA value is achieved on training data set and afterwards the best NNW training algorithm is selected.

4 Obtaining the Experimental Data Set

For testing and optimization of proposed methods and algorithms for automated classification of BPBS the clinically verified database of BioRascan BRL signals for subjects with SAS collected during parallel registration of full-night polysomnography (PSG) on the base of Sleep Laboratory of Almazov Federal Heart, Blood and Endocrinology Centre was used [4].

For forming of BPBS attribute vectors both BRL signal quadratures were used with the same length of 128 counts corresponding to 12.8 seconds satisfying the recommendations for screening of SAS [2]. For BRL signals at sampling rate of $f_s = 10.0Hz$ with maximum breathing frequency [6] not exceeding $f_m = 1.0Hz$ the OLD value came to $L_0 = 3$ providing 16 components in the structure of BPBS attribute vectors.

The experimental data set included 240 realizations of BPBS related to the three classes (OSA, CSA, NCS) in the following proportion:

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

5 Results

In accordance with proposed MEC and ODL criterions basis Symlet 13 from the general class of wavelets with compact support on the 3rd level of wavelet decomposition was considered to be the best for feature extraction. The estimate of MEC itself should be considered effective and consistent. Calculation of MCA criterion revealed the optimal number of NNW hidden neurons equal to 9 which also corresponded to the upper boundary limit estimated from Kolmogorov-Hecht-Nielsen theorem. Levenberg-Marquardt training algorithm should be considered the best for the proposed classifier providing the mean classification accuracy not less than 84% with type II error not exceeding 8% for SDB patterns, satisfying medical recommendations.

Acknowledgements. The research was performed in the framework of the "Active and Passive Microwaves for Security and Subsurface imaging (AMISS)" EU 7th Framework Marie Curie Actions IRSES project (PIRSES-GA-2010-269157) and supported by the grants of the Ministry of Education and Science of Russian Federation and Russian Foundation for Basic Research.

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