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CLASSIFICATION OF RESPIRATORY SOUNDS BY USING AN ARTIFICIAL NEURAL NETWORK

M.C. Sezgin, Z. Dokur, T. Ölmez, M. Korürek
Department of Electronics and Communication Engineering,
Istanbul Technical University, Istanbul, Turkey
e-mail: zumray@ehb.itu.edu.tr

Abstract-**In this paper, a classification method for respiratory sounds (RSs) in patients with asthma and in healthy subjects is presented.**

Wavelet transform is applied to a window containing 256 samples. Elements of the feature vectors are obtained from the wavelet coefficients. The best feature elements are selected by using dynamic programming. Grow and Learn (GAL) neural network is used for the classification.

It is observed that RSs of patients (with asthma) and healthy subjects are successfully classified by the GAL network.

***Keywords*-Respiratory Sounds, Classification of Biomedical Signals, Artificial Neural Network.**

I. INTRODUCTION

Sounds heard over the chest wall are useful diagnostic tools for pulmonary diseases. Amongst other diagnostic methods is auscultation an attractive one with its relative simplicity and cheapness. Modern lung sound analysis, which began in the last four decades, is focused on digital sound processing and graphic representation of the signals [1,2]. Computerized lung sound analysis and diagnosis is the main goal of the researches in this field. Thus, an objective and reliable diagnostic tool for the detection of pulmonary diseases is aimed. In this work, RSs belonging to 10 pathological and 10 healthy subjects are examined.

In order to make a reliable comparison between the results of the investigators, it is important to make clear the measurement equipment [3]. Before recording, an elastic band is wound around the chest wall to hold ES (electronic stethoscope, Cardionics Inc.) tightly on the recording site. The recording site is chosen as lower part of the scapulas at the back. To avoid the friction noise, a very thin, porous, sponge like material is settled between the skin and the ES. The ES has a band-pass filter having a range from 50 Hz to 2000 Hz. The RS obtained by the ES are digitized by a 16-bit sound card of a personal computer at 22050 Hz.

II. METHODS

Decision-making is performed in three stages: Normalization process, feature extraction, and classification by the artificial neural network.

In this study, frequency of the RS signals obtained by the ES are decimated at 1378.12 Hz and analysed within windows that contain 256 discrete data. Figs. 2(a) and (b) show short time Fourier spectrums (STFS) of the RS signals through single respiration (one expiration and one inspration state) for two subjects, one healthy and the other with asthma, respectively. Discrete Fourier spectrums of the windowed signals show that expiration state gives more information about the asthma. Spectrum of the RS signal is divided into sub-bands to extract the discrepancies between asthmatic and normal subjects.

At first, the RS signal obtained from a real-time measurement equipment is splitted into windows of 256 discrete data; each window is considered as a vector in a 256 dimensional space. For the two classes (normal and asthma cases), two different sets are formed for training and test purposes. Each set contains 300 vectors (150 vectors from each class) of 256 dimensions. Second, the vectors in the data sets are normalized, and features for each normalized vector are extracted. After the feature vectors are formed, they are applied to the input of the neural network for training or classification purposes. After the training, neural network decides whether RS signal in a window contains information about asthma. The overall block diagram of the decision-making system is shown in Fig. 1.

A. Normalization Process

Feature extraction processes are affected by the peak-to-peak magnitudes, the offset of the signal in the windowed RS signal. These effects are due to physiology, sex and age of the patient, and parameters of the measurement system. In the study, prior to the feature extraction process, power of the windowed RS signals are computed so that the rms values of the wavelet coefficients are normalized.

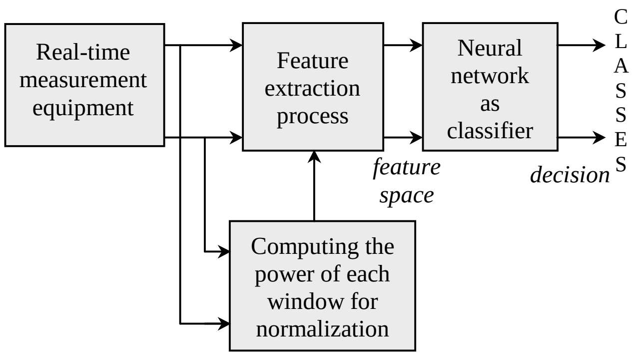

Fig. 1. Decision-making blocks.

B. Feature Extraction Method

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Abstract

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Because RS signals are non-stationary, the discrete wavelet transform is involved for the sub-band analysis.

Wavelet coefficients are determined by using Daubechies-2 wavelets [4]. For each RS signal, wavelet detail coefficients at the first five levels (five sets of coefficients), and wavelet approximation coefficients at the fifth level (one set of coefficients) are computed. A total of six rms values for the six wavelet coefficient sets are computed, and they will be used to form the feature vectors. The best features are determined by applying divergence analysis [5] to the training sets of 300 vectors. Divergence analysis enables to determine the best features which increase the classification performance, and also it gives information to determine the dimension of the feature vectors. From the calculated six rms values, a subset of the best 3 coefficients is searched by using dynamic programming (DP) [5] according to the divergence values. The ordering of the elements in each feature vector is as follows:

$$P=[r_{d1}, r_{d2}, r_{d3}, r_{d4}, r_{d5}, r_{a5}]$$

$$\frac{k_1 \quad k_2 \quad k_3 \quad k_4 \quad k_5 \quad k_6}{r_{d1} \quad r_{d3} \quad r_{d5} \quad r_{d2} \quad r_{d4} \quad r_{a5}} \tag{1}$$

$$\mathbf{K}=[r_{d1}, r_{d3}, r_{d5}]$$

In (1), P is the feature vector contained six rms values, r_{di} is the rms value of the detail coefficients at the *i*th decomposition level, r_{a5} is the rms value of the fifth level approximation coefficients, and **K** is the three-dimensional new feature vector. With the features found in the order as shown above, divergence value is maximised at 2.287 value.

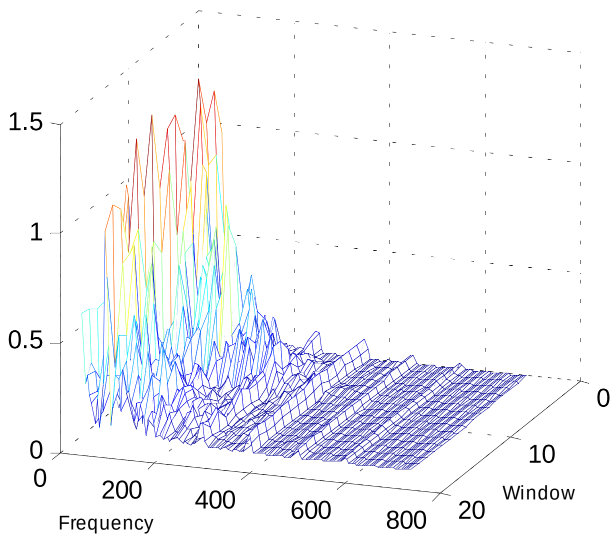

Fig. 2. (a) STFS of the normal RS.

C. Artificial Neural Networks

Selection of an appropriate classifier is one of the most important tasks for any decision-making system. In the study, an artificial neural network (ANN) is used as the classifier to increase the classification performance. There are four reasons to use an ANN as a classifier: 1) Weights representing the solution are found by iteratively training, 2) ANN has a simple structure for physical implementation, 3) ANN can easily map complex class distributions, 4) Generalization property of the ANN produces appropriate results for the input vectors that are not present in the training set.

Multi-layer perceptron[6] is frequently used in biomedical signal processing [7].It is observed that multi-layer perceptron has three disadvantages: 1) Back-propagation algorithm takes too long time during learning, 2) The number of nodes in the hidden layers must be defined before the training. The structure is not automatically determined by the training algorithm, 3) Back-propagation algorithm may be caught by local minima, which decreases network performance. We observed these disadvantages in the previous study [8]. Especially, the number of nodes in the hidden layers could be defined after many trials, which took too long time. Moreover, the classification performance was not satisfactory.

Therefore, multi-layer perceptron is not used in the comparisons with other networks and GAL network [9] is proposed to classify the RSs in this study. It is observed that GAL network gives high classification performance, and the number of nodes of the network is determined automatically by its training algorithm, and training takes considerably short time.

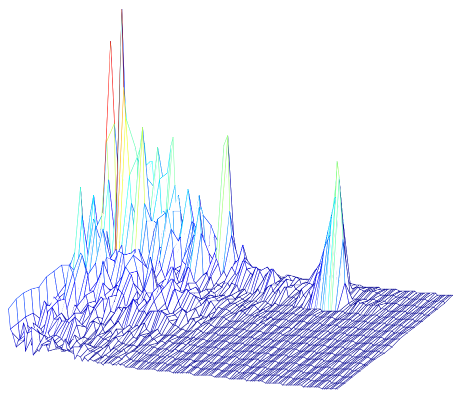

Fig. 2. (b) STFS of the RS in a patient with asthma.

III. Computer Simulations and Conclusion

Figs. 3(a) and (b) show RS signals of one respiration cycle (one expiration, one inspiration state) of a healthy subject and a patient with asthma, respectively. Each RS signal in Fig. 3 contains 4096 discrete data (16 windows). A three-dimensional feature vector is formed for each window. Elements of the feature vectors represent the power of the signal in subbands. After normalizing the feature vectors, they are presented to the input of the GAL network.

Ten records from healthy subjects and from patients with asthma are used to form the training set. Each record contains five respiration cycles. Three feature vectors are extracted from a single respiration cycle. In this study, RSs are separated into two classes: 1) Normal RSs, 2) RSs with asthma. Training set contains 300 feature vectors, 150 feature vectors belonging to each class. Test set also contains 300 feature vectors, and it is different from the training set.

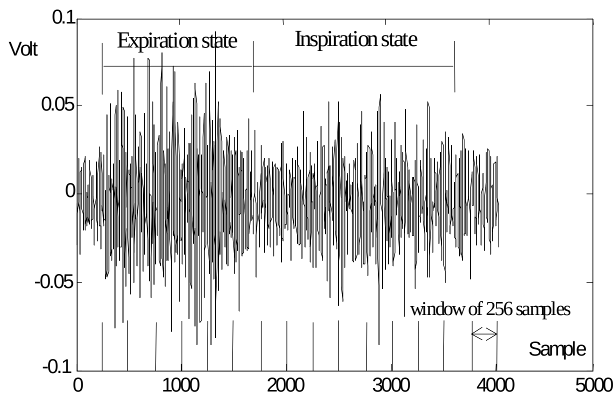

Fig. 3. (a) RS of a healthy subject.

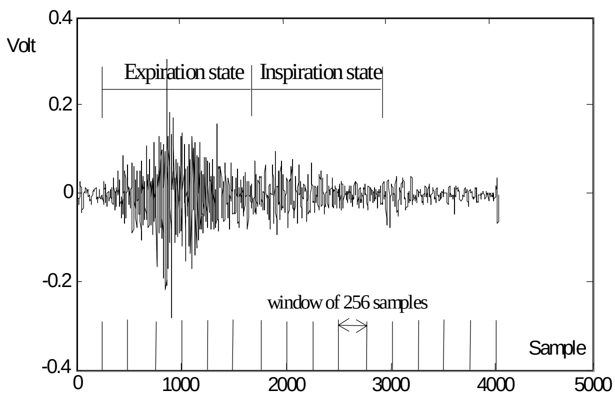

Fig. 3. (b) RS of a patient with asthma.

Table I shows the classification results of the GAL. Testing time contains normalization, feature extraction and classification process for RS signal in single window. GAL network successfully classifies the respiratory sounds by using a few nodes.

TABLE I
CLASSIFICATION RESULTS OBTAINED BY THE GAL

	Classification results of GAL
Number of nodes	2
Training time	<1 second
Testing time	<0.5 second
Classification of RS with asthma	%98
Classification of Normal RS	%98

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