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Classification of Wheeze Sounds Using Wavelets and Neural Networks

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Abstract. Wheezes are one of the most important adventitious sounds in pulmonary system. They are observed in asthma, chronic obstructive pulmonary disease (COPD) and bronchitis. The purpose of this research is to analyze wheeze sounds and classify them as monophonic and polyphonic types. Data is acquired in normal hospital conditions by a typical stethoscope. Various statistical features are extracted from coefficients of 7 different wavelets. Then according to ROC curves, groups of more powerful features are selected. We use multilayer perceptron (MLP) neural network as a classifier. The experimental results show that using a set of 15 selected features and a 15-45-2 MLP network, wheeze sounds could be classified with 89.28% accuracy.

Keywords: Wheeze, Respiratory sounds, Wavelet transform, Neural networks, COPD, Asthma.

1. Introduction

Respiratory diseases including asthma, COPD and bronchitis cause severe medical problems for large crowd of people. From the invention of stethoscope by Laennec in 1821, acoustic analysis has been the primary assessment technique for physicians [1]. It's an easy, fast, not expensive and noninvasive way to evaluate and diagnose patients with lung sounds and needs minimum cooperation [1-2]. It is especially useful for all those who could not perform conventional respiratory function tests. Therefore it is still the most frequently used medical device today.

Using the stethoscope has disadvantages: it is a subjective method that depends on physician's experience, skill and auditory training [2-3]. It lacks a method of recording, has insufficient sensitivity and offers no quantitative description. Moreover, the stethoscope attenuates frequency components of respiratory sound signal above 120 Hz. The human ear structure is not very sensitive to the lower frequency band that remains. Using signal processing techniques, a more unified and objective diagnosis that would not experience human diagnosis drawbacks is attainable. Researchers have used different techniques to extract suitable features for classification of respiratory sounds for diagnosing between healthy cases and patients with various respiratory diseases [2-3].

Various internal organs produce many sounds. Sounds created in the pulmonary system (airways and lungs) are called respiratory sounds. They are made because of airflow during inspiration and expiration. They provide a strong source of information for assessing the condition of the pulmonary system [4-5]. Respiratory sounds are classified into normal and abnormal groups based on their acoustic properties [3]. Adventitious breathing sounds refer to extra sounds during a normal breathing cycle. Wheezes and crackles are two adventitious sounds commonly related with respiratory diseases. According to definition of ATS (American Thoracic Society) wheezes are continuous musical sounds that are longer than 250 ms, with a dominant frequency of 400 Hz or

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more [6-7]. They are most heard in the end of inspiration or early expiration phase. Wheezes can be caused by airway narrowing and the increased secretions. As a collapsed airway lumen gradually opens during inspiration or progressively closes during expiration, wheezes are produced [6]. Wheezes are classified to polyphonic and monophonic types. It is often inferred that polyphonic wheezes are associated with disease of small airways and monophonic wheezes are associated with disease of larger airways [6]. Usually wheezes are heard in diseases like congestive heart failure, asthma, pneumonia, chronic bronchitis, COPD and emphysema [1, 6].

Previous researches show that frequency analysis can be used to distinguish between normal and wheeze sounds [8-9]. Autoregressive modelling (AR) [3, 10], wavelet transform [2, 11-12] and Mel frequency cepstral coefficients (MFCC) are also used for feature extraction to discriminate between wheeze and non wheeze pulmonary sounds [3-4]. For classification and prediction of breathing sounds artificial neural networks have also been used [2-3, 11, 13]. The best results for wheeze and normal sounds classification were obtained with Gaussian Mixture Model (GMM) [3-4, 14] and MFCC in 2009 [3]. To the best of our knowledge there are no reports concentrating on discriminating between monophonic and polyphonic types of wheeze sounds. In this research we will try to classify these types of respiratory sounds using a group of suitable features extracted from the breathing sounds.

2. Materials and methods

2.1. Data

Respiratory sounds were recorded from patients using an electronic stethoscope at the Pulmonary Department of Loghman Hakim hospital in Tehran. Data is then transmitted to a computer for display and analysis. The sampling frequency is 8 KHz. The signals are captured from 140 different subjects with typical COPD and asthma. It consists of 77 polyphonic and 63 monophonic wheeze sounds. Their clinical diagnosis was based on pulmonary tests, patient symptoms, auscultation, chest X-ray and clinical laboratory test results evaluated by respiratory physicians. The classifications of the wheezes were done by a senior physician.

2.2. Analysis

Pattern recognition consists of two steps. At the first step features are extracted from the signals in such a way that represent the signal very well. These features should contain all important information about the signal. Then according to a tradeoff between required accuracy and computation cost, a smaller number of meaningful features are selected. The second step is the classification, i.e. a specific pattern is allocated to a class based on the characteristic features selected for it. In this study the data is first pre-processed. Then during the feature extraction and feature selection phase a group of appropriate features are obtained. Finally using a neural network, the wheeze sounds are classified.

All signals are first go through amplitude normalization. Sharp or sudden changes in physiological signals can represent abrupt faults. Besides, noise and outliers are important problems in physiological signals. So there is a need for filtering out these unwanted parts of the captured signal. The moving average is the easiest and most common digital filter. It is usually applied to time series data to smooth out fluctuations. The parameter of the moving average is the window size which depends on the application. Using a moving average filter removes large amplitude fluctuations between samples and a much smoother signal is produced [5].

Respiratory sounds are non-stationary and are stochastic signals inherently [1-2]. Fourier transform (FT) loses time domain data of the signal and so does not provide enough information for this kind of signal. Short Time Fourier Transform (STFT) overcomes this drawback by converting signal to a two-dimensional space of time and frequency using a single fixed window that produces fixed resolution in time and frequency domains. Wavelet analysis provides a tool with varying resolution in both time and frequency. With changing window size in wavelet transform (WT), a multi-resolution view of the signal is obtained in witch dominant modes of the signal and how those modes would change in time are determined simultaneously. Continuous wavelet transform (CWT) is defined by:

$$CWT(a,b) = \int_{-\infty}^{+\infty} x(t)\psi^*_{a,b}(t)dt$$

where x(t) is the analyzed signal, a represent the scaling factor (dilatation/compression coefficient), b denotes translation along the time axis (shifting coefficient) and

$$\psi^*_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}).$$

In other words, the function $\psi^*_{a,b}$ is obtained by shifting and scaling the prototype wavelet ψ.

Calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data. Therefore, the Discrete Wavelet Transform is often used. The DWT decomposition of a signal x[n] is implemented using a complementary low-pass/high-pass filtering. The signals are then down-sampled by 2. The outputs of the high-pass filters are details and those of the low-pass filters are approximations [15].

In this work wheeze sounds are described with seven details, d_1 to d_7, and one approximation, A_7. By extracting statistical features from wavelet coefficients, the input space dimensionality will decrease. Six statistical features were extracted from the wavelet coefficients.

- Mean of the absolute values in each subband (μ_{di}).
- Average power in each subband (p_{di}).
- Standard deviation in each subband (σ_{di}).
- Ratio of the absolute mean values of adjacent subbands (μ_{di}/μ_{di+1})
- Skewness in each subband (sk_{di}).
- Kurtosis in each subband (ku_{di})

Mean and average features represent the frequency distribution of the signal and the standard deviation and ratio of the absolute mean values of adjacent sub bands show the amount of changes in frequency distribution. Skewness is a measure of the asymmetry of the probability distribution of a real-valued signal and kurtosis measures the "peakedness" of the probability distribution of a real-valued signal.

An important issue is the evaluation of extracted features. Best features should be selected based on their discrimination power. ROC curve could be used to assess features. The more the area under the ROC curve, the more powerful is the feature.

The classifier is an artificial neural network. A Multilayer Perception (MLP) consists of an interconnected group of artificial neurons. MLP is an adaptive system with a training algorithm that changes weights to minimize the error between desired and network's output. The training process is continued until a predefined minimum of the output error is reached. In this study the Levenberg–Marquardt (LM) training algorithm is used.

3. Results

After normalization and using a moving average filter with a window size of 25 samples, DWT is applied to the signals. Seven different wavelets consisting Haar, Symmlet of order 8, Daubechies of orders 2, 8 and 10 and Bi-orthogonal of orders 1.5 and 2.8 are used. In this way 46 features are extracted from every signal using each wavelet. The features are then ranked based on the area under the ROC curve. The first 5, 10 and 15 features are selected for classification. Networks with 5-15-2, 10-30-2 and 15-45-2 structures containing sigmoid hidden neurons and linear output neurons are used as classifiers respectively. Accuracy results achieved by various ANN structures are shown in figure1.

All features from different wavelets are then combined and ranked based on the ROC criteria and again the first 5, 10 and 15 features are selected for classification with the same NN structures. The results are shown in the last column of the figure1.

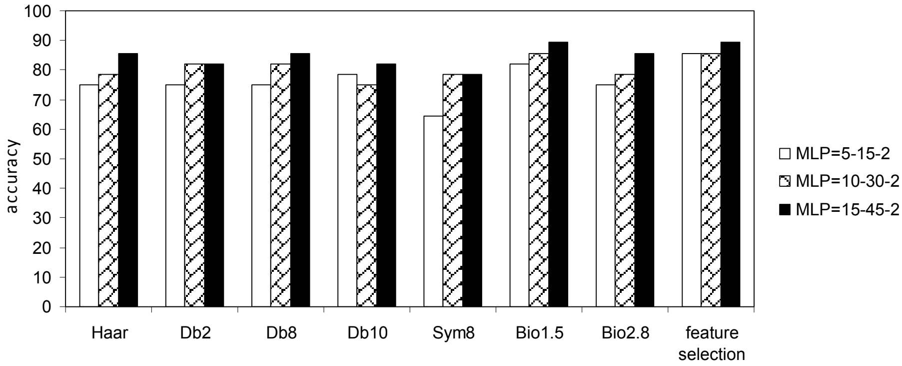

Fig. 1: Performance of wheeze classifiers based on the used features.

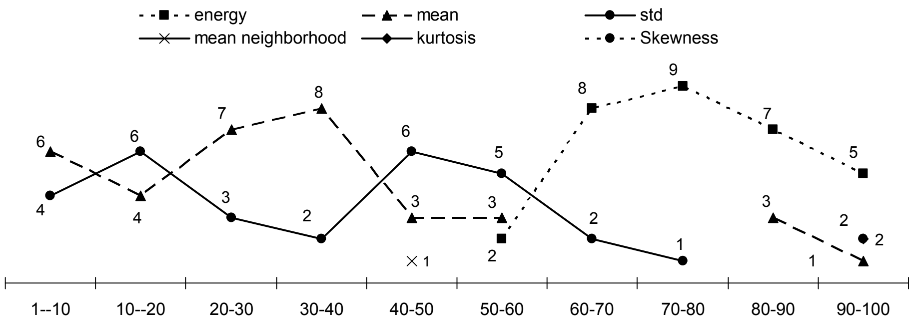

Fig. 2: Feature distribution in ordered groups of first 100 best features.

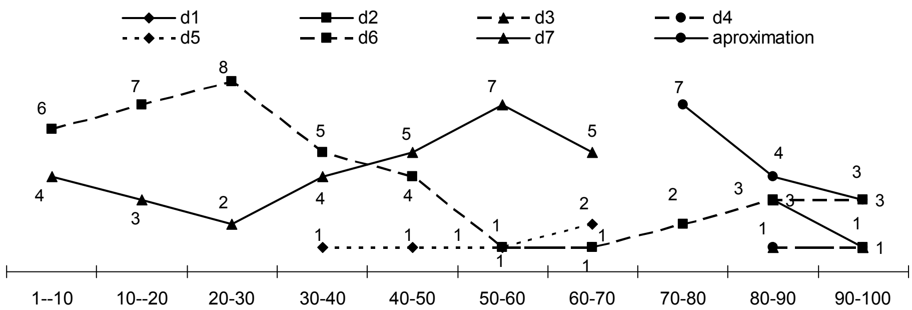

Fig. 3: Subband distribution in ordered groups of first 100 best features.

To evaluate the performance of different feature types, the presence of each feature in the first, second, …, tenth group of 10 best features is tested. Figure 2 shows the results. At the other hand, the contribution of each subband to the classification process is evaluated by considering the number of features each contribute to the ordered groups of 10 features. The results are shown in figure 3.

4. Discussion and Conclusion

Bi-orthogonal 1.5 offers better accuracy than the other wavelets. Also comparison of the results of db8 and db10 shows that higher order wavelets do not produce better results. Comparing bio1.5 and bio2.8 confirms this conclusion as well. It can be seen that the selected set of features among all wavelets coefficients results in a better classification of wheeze sounds. The price is a more computational cost. By comparing features contribution we conclude that mean, standard deviation and energy appear more often in the first 100 features. Besides, mean and standard deviation appear in high priority feature groups more than the other features. Considering subbands, d6 and d7 subbands and also the last approximation contribute more to classification.

Results of this work are obtained using data acquired in normal hospital conditions by a typical stethoscope, while other studies normally use special conditions and apparatus to gather data.

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