Classification of Asthmatic Breath Sounds by Using Wavelet Transforms and Neural Networks

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***Abstract*—In this study, respiratory sounds of asthmatic patients and healthy individuals are analyzed and classified to diagnose asthma. Normal and asthmatic breath sound signals are divided into segments which include a single respiration cycle as inspiration and expiration. Analyses of these sound segments are carried out by using both discrete wavelet transform (DWT) and wavelet packet transform (WPT). Each sound segment is decomposed into frequency sub-bands using DWT and WPT. Feature vectors are constructed by extracting statistical features from the sub-bands. Artificial neural network (ANN) is used to classify respiratory sound signals as normal and level of asthmatic diseases (mild asthma, moderate asthma and severe asthma). The classification results of DWT and WPT are compared with each other in terms of classification accuracy.**

***Index Terms*—respiratory sounds, discrete wavelet transform, wavelet packet transform, artificial neural network**

I. Introduction

Asthma is one of the chronic lung diseases that inflames and narrows the airways. This disease is often seen in many people over the world and poses major medical problems. For this reason, early detection and treatment of asthma disease is one of the most important medical research areas [1]. Asthma and other pulmonary disorders are investigated in several ways such as a medical history, physical examination, chest X-ray, respiratory auscultation etc. Among these, the most common diagnostic method is auscultation [1] because auscultation is an inexpensive, efficient, easy to apply and harmless for patient.

Auscultation is the medical term of listening to sounds arising within organs such as lung. It usually is carried out using stethoscope by physicians. Auscultation both gives direct information about the function of lung [2] and provides close patient-physician interaction [3]. Because of many benefits, auscultation is considered to be a very useful tool.

However it has major limitations and problems. There are many factors that influence auscultation, including the response of stethoscope and external noise [4]. Stethoscope may be unreliable in noisy environments such as ambulance, a busy emergency room etc. The proper diagnosis also requires significant training and experience of the medical personnel [5].

In last decades, with the advent of computer technology and data processing methods, researchers have tried to parameterize pulmonary sounds with an aim to make auscultation a more objective and valuable diagnostic tool [6]. During the last two decades, much research has been carried out on computer-based respiratory sound analysis [7]. A large part of these researches include acquisition, filtering, feature extraction, spectral analyses and classification of respiratory sounds. In literature, frequency analyses methods [8]-[10] such as Fourier based methods, parametric methods such as AR methods [11], [12] and time-frequency analysis methods such as wavelet transforms [2], [13] have been used mostly to analyze respiratory sounds. For the classification of these sounds, usually machine learning algorithms such as artificial neural networks, k-nearest neighbor (k-NN) are used.

In this study, asthmatic and normal respiratory sound signals are recorded from patients with asthma in different degrees and normal subjects. Later, the signals separated as inhalation and exhalation sound signals. Each inhalation and exhalation sound record consists of more than one and different number of respiration cycle. Both for these reasons and due to insufficient respiratory sound records, recorded sounds are divided into segments. In this way, each segment contains of equal number of respiration cycle as one inhalation or exhalation phase. Every sound segment is evaluated and processed as a separate pattern.

Wavelet transforms; discrete wavelet transform (DWT) and wavelet packet transform (WPT) are used to analyze the sound segments, because of their high success ratios in previous literature studies. The sound segments are decomposed into frequency sub-bands through DWT and WPT. Feature vectors which are applied as inputs to artificial neural networks (ANN) are created by extracting statistical features from sub-bands. ANN is used to classify the respiratory sounds segment. Then,

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performances of both DWT and WPT were compared according to classification results in terms of classification accuracies. The block diagram of this study is shown in Fig. 1.

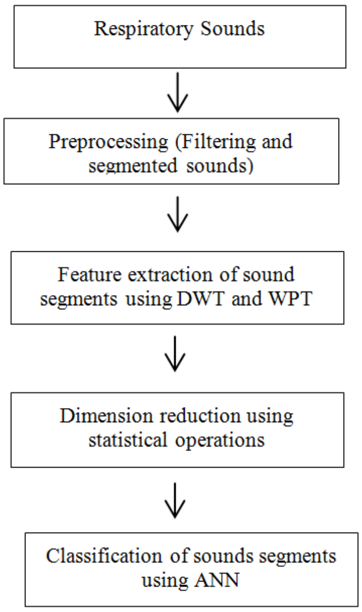

Figure 1. Block diagram of this study.

II. Materials and Methods

A. Acquisition of Respiratory Sounds and Preprocessing

In this study, respiratory sound signals acquired using Sony ECM T-150 microphone (at 8kHz) with a cap. Working method of this microphone in one direction and microphone is used by mounting onto stethoscope head.

Sound signals are recorded via the microphone from patients who had severe asthma, moderate asthma, mild asthma and normal subjects. The sound signals are recorded right basal and left basal. Duration of sound recording nearly 11-12 sec and include more than one and different numbers respiration cycles.

Because of mix of heart, muscle, and other sounds which come from lung not belonging to respiratory disease, recorded respiratory sounds are not completely distinguishable. Hence we use low-pass and high-pass filter to filter these unwanted sounds. In literature respiratory sound signal frequency band is in between 100-2000Hz. In filtering stage filter the signals whose frequencies below 100Hz by using high-pass filer and above 2000Hz by using low-pass filter. Following the analog and digital processes, the signals are separated and grouped as inhalation and exhalation sound signals belonging to 11 persons.

The amount of respiratory sound records is not enough for proper classification due to few patients. Each inhalation and exhalation sound divided into segments to include an inhalation and an exhalation phase of respiratory cycle. Each sound segment is considered a pattern and processed separately.

B. Feature Extraction Methods

Wavelet Transform (WT) is one of the well-known and useful tool for signal processing. By decomposing signals into elementary building blocks that are well localized both in time and frequency, the WT can characterize the local regularity of signals [14]. It provides an alternative to Fourier transform (FT). In particular, WT is of interest for the analysis of non-stationary signals [15] because FT does not provide enough information for non-stationary signals. FT determines only the frequency components of a signal, but not their location in time [2]. To overcome problem of time, short time Fourier transform (STFT) was developed. However this method uses single window. WT emerged as an alternative to Fourier transforms. In contrast to STFT, WT uses short windows at high frequencies and long windows at low frequencies [15].

Discrete wavelet transform is a wavelet transform. It is used to reduce the computational burden of continuous wavelet transform [16]. DWT have been widely used for analyzing non-stationary signals, and provides time-frequency representation of the signals [17]. In discrete wavelet transform (DWT), a signal is decomposed into low frequency band (approximation coefficients) and higher frequency band (detail coefficients).Low frequency band is used for further decomposition [18]. Obtained coefficients which represent signal are used for network training and classification process in many signal processing applications. DWT structure is shown Fig. 2.

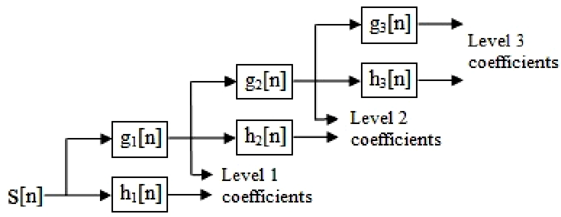

Figure 2. DWT structure.

DWT is expressed with equations as in (1), (2) and (3). S is a signal and ψ is a main wavelet.

$$W(j,k)=\sum_{j}\sum_{k}S(k)2^{-j/2}\psi(2^{-j}n-k) \tag{1}$$

where h represents high pass filter and g represents low pass filter in following equations.

$$CA1=\sum_{k}S[k]g[2n-k] \tag{2}$$

$$CD1=\sum_{k}S[k]h[2n-k] \tag{3}$$

Wavelet packet transform (WPT) was proposed by Coifman and Wickerhauser [18], can be regarded as an extension of the wavelet transform. In wavelet packet transform, both lower and higher frequency bands are decomposed into two sub-bands. Thereby wavelet packet gives a balanced binary tree structure. WPT tree structure with 3 levels is shown Fig. 3. The WPT suits signal processing, especially nonstationary signals because the same frequency bandwidths can provide good resolution regardless of high and low frequencies [19].

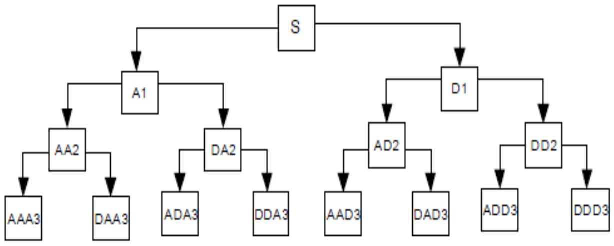

Figure 3. WPT tree structure.

C. Feature Extraction of Respiratory Sounds

In this study, both DWT and WPT are used to analyze respiratory sounds. Firstly, each respiratory sound segment is decomposed into sub-bands using DWT. The number of levels of decomposition are determined as 7. In this case, sound signals are divided into D1-D7 detail sub-bands and A7 approximation sub-band. The accuracy of classification depends on type of the selected wavelet [16]. In this study, Daubechies wavelet of order 5 (db5) has been chosen as wavelet type. Fig. 4 shows that approximation and detail sub-bands of an asthmatic sound segment when decomposition level is chosen 2 and wavelet type DB5. Wavelet coefficients of D2-D6 detail sub-bands are considered as feature vectors of sound signal segment.

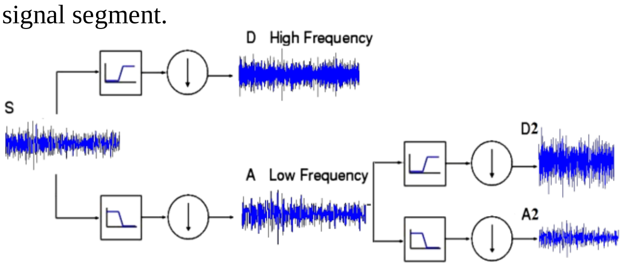

Figure 4. 2-Degree approximation and detail sub-bands of an asthmatic sound segment.

Secondly, WPT is applied to each sound segment. The number of levels of decomposition are determined as 7. As in the discrete wavelet transform, wavelet type is selected as the DB5 in wavelet packet transform. Sub-bands are selected to represent sound segment. Fig. 5 shows decomposition of the sound segments using WPT and selected sub-bands as underlined. Coefficients of these sub-bands in the tree are considered as feature vectors of segments.

Dimension of obtained feature vectors are too large in both DWT and WPT. Therefore, statistical features are extracted from D2-D6 detail sub-bands for DWT and same statistical features are extracted from selected sub-bands of tree for WPT.

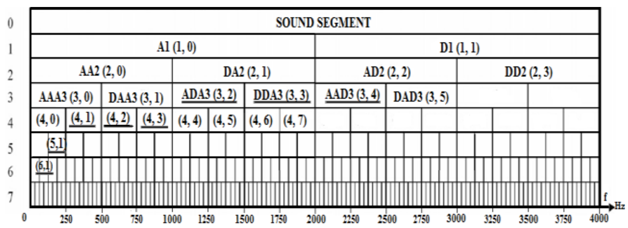

Figure 5. Decomposition of sound segment using WPT.

Used statistical features are:

1. Mean of the absolute values in each sub-band
2. Max of the absolute values in each sub-band
3. Average power spectra of the wavelet coefficients in each sub-band
4. Standard deviation of the wavelet coefficients in each sub-band
5. Ratio of the absolute mean values of adjacent sub-bands
6. Zero crossing count in each sub-band

Mean indicated by μ is the average value of a signal. Mean measure of the central tendency and represents a probability frequency distribution of signal. The mean is found by adding up all of samples together, and divide by length of signal. Its mathematical form is as in (4). *Xn* represents signal.

$$\mu = \frac{1}{N}\sum_{n=1}^{N} X_n \tag{4}$$

Equation (5) represents mean of absolute values.

$$\mu = \frac{1}{N}\sum_{n=1}^{N} |X_n| \tag{5}$$

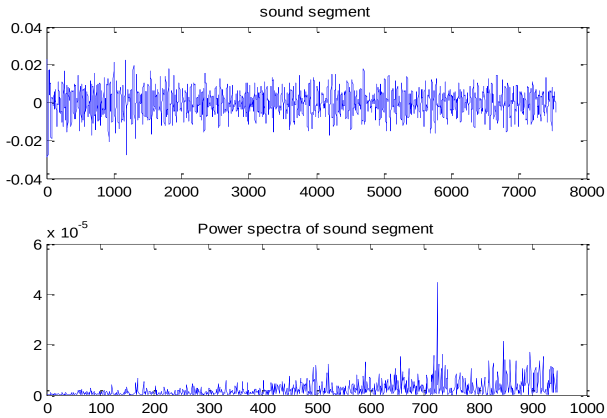

Figure 6. Power spectrum of D2 coefficients belong to asthmatic sound segment.

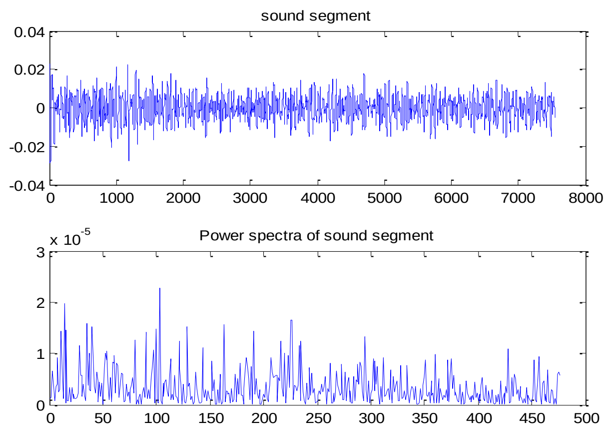

Figure 7. Power spectrum of coefficients of DDA3 sub-band of WPT tree belongs to asthmatic sound segment.

For a given signal, the power spectrum gives a plot of the portion of a signal's power (energy per unit time) falling within given frequency bins. The most common way of generating a power spectrum is by using a discrete Fourier transform [20], [21]. Here power spectrum of wavelet coefficients were generated using Fast Fourier Transform (FFT). Fig. 6 shows asthmatic sound segment and power spectrum of D2 detail coefficients belonging to this segment using FFT and DWT. Power spectrum of coefficients of DDA3 sub-band of WPT tree belonging to asthmatic sound segment and this segment is shown Fig. 7 using FFT.

In this study, power spectra of all sub-bands were found by FFT. And then the statistical feature was obtained by averaging power spectrum values.

Standard deviation is indicated by σ. Standard deviation measures the amount of variation or dispersion from the average. It represents the amount of changes in frequency distribution. It is expressed as in (6).

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(xi-\mu)^2} \tag{6}$$

Zero Crossing (ZC) counts the number of times that signal crosses zero. ZC can be calculated as in (7).

$$ZC = \sum_{n=1}^{N\text{-}1}[sgn(x_n \times x_n + 1) \cap |x_n - x_n + 1| \geq 0] \tag{7}$$

Features 1-3 represent the frequency distribution of the signal and the features 4, 5 and 6 the amount of changes in frequency distribution. The resulting statistical features were used as inputs to artificial neural network for classification.

D. Classification Using Artificial Neural Network

Artificial neural network (ANN) is used commonly in many areas such as recognition and classification of biological signals, voice recognition, and fingerprint recognition, automatic vehicle control, monitoring and modeling [16]. ANN is an interconnected assembly of simple parallel processing elements, units or nodes, whose functionality is loosely based on animal neuron [22]. The Multi-layer perceptron (MLP) is the most widely used type of neural network. It is both simple and based on solid mathematical grounds [23]. The most frequently used training algorithm for MLP is the backpropagation (BP) algorithm [2]. The BP training algorithm has generalized delta learning rule which is an iterative gradient algorithm designed to minimize the root mean square error between the actual and the desired network outputs [24]. BP algorithm can be described two phases; propagation and weight update [24].

Each propagation consists of the following steps:

1) Forward propagation: Let a training example be denoted by [x(n), d(n)], with the input vector x(n) applied to the input layer to generate output vector y(n) and the desired (or target) response vector d(n) presented to the output layer. Then, for every node in the output layer, the error is calculated as in (8).

$$e_j = d_j(n) - y_j(n) \tag{8}$$

where *j* is the node in the output layer.

2) Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.

For each weight-synapse includes the following steps:

1) Multiply its output delta and input activation to get the gradient of the weight.

2) Subtract a ratio (percentage) of the gradient from the weight.

In this study, ANN with back propagation algorithm is used to classify respiratory sounds into four class namely normal, mild asthma, moderate asthma and severe asthma. Statistical features are used as inputs into network. Input layer consists of 30 neurons for feature vectors obtained using DWT. The layer contains 48 neurons for feature vectors obtained using WPT. 23 neurons is used in hiddenlayer gave the best performance. Output layer of neural network comprise 4 neurons for both DWT and WPT analysis. ANN structure which we use in this study is shown in Fig. 8.

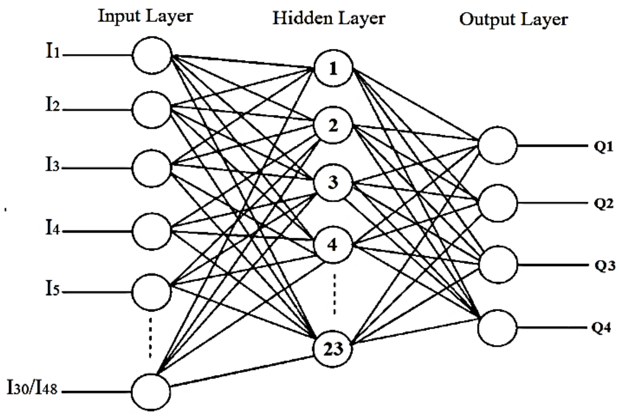

Figure 8. Used MLP structure.

Q1, Q2, Q3, Q4 outputs represents respectively normal, moderate asthma, mild asthma and severe asthma classes. In this study, orange canvas toolbox was used for ANN classifier.

III. Experiments and Results

Respiratory sound signals are segmented to comprise one exhalation or inhalation phase. Each sound segment is considered as a separate pattern. The sound segments are decomposed into sub-bands using DWT and WPT to create feature vectors of sounds. 6 statistical features extracted from sub-bands to reduce dimension of feature vectors and to represent sound signal segments.

ANN is used to classify normal and different level of asthma. Classification process is separately performed for right basal and left basal as well as inhalation (breathing in) and exhalation (breathing out) sound signal segments. Orange toolbox is used for ANN with 0.1 regularization factor, 1000 iteration and 10 cross validation.

In this study, features vectors are created by using DWT, WPT and then statistical operations. Classification process is carried out with these feature vectors. Performances of both DWT and WPT as feature extraction methods are compared in terms of classification accuracies. Table I shows that percentages of classification accuracies for normal and three different asthmatic classes (Mild Asthma, Moderate Asthma, Severe Asthma), when DWT is used for feature extraction and ANN is used for classification. Percentages are seen in Table II using WPT and ANN.

TABLE I. CLASSIFICATION ACCURACIES OF NORMAL AND THREE DIFFERENT ASTHMATIC CLASSES USING DWT AND ANN

Basals	Classification Accuracies (%)	
	DWT	
	Inhalation	Exhalation
Right Basal	91.67	76.67
Left Basal	90.00	86.67

TABLE II. CLASSIFICATION ACCURACIES OF NORMAL AND THREE DIFFERENT ASTHMATIC CLASSES USING WPT AND ANN

Basals	Classification Accuracies (%)	
	WPT	
	Inhalation	Exhalation
Right Basal	90.00	80.00
Left Basal	88.33	81.90

Results (Table I and Table II) show that DWT, WPT analysis methods and ANN classifier give promising results for detection of asthma disease. Accuracy of correct classification for DWT and WPT methods is quite high in especially inhalation sounds analysis. As seen in Table I and Table II that compared with WPT; DWT has slightly higher performance except right basal exhalation phase. However, if different sub-band selections are made from the WPT tree, classification accuracies can be higher in analysis of respiratory sounds using WPT. Even in this case, the DWT is more advantageous than WPT in terms of processing load and computational time. So DWT is used more frequently for analysis of respiratory sounds.

IV. CONCLUSIONS

Respiratory sound analysis using signal processing techniques is important to diagnose pulmonary diseases such as asthma. There are many studies about analysis of respiratory sounds. It is seen in these studies that Wavelet transforms and Neural Networks give high success ratio. So, we use DWT, WPT analysis techniques and ANN classifier to analyze our respiratory sounds. We compare these analysis techniques in terms of classification accuracies. As a result of, we have seen from results that DWT has slightly better than WPT in our study. Also we have seen that inhalation sounds analyses give us more useful information about asthmatic diseases than exhalation sounds. The results obtained are very promising to detect asthma disease. However, further experimental work is required, especially with a larger database of respiratory sound, to improve the classification results.

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