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Multi-channel Classification of Respiratory Sounds

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***Abstract*—In this study, respiratory sounds of pathological and healthy subjects were analyzed via frequency spectrum and AR model parameters with a view to construct a diagnostic aid based on auscultation. Each subject is represented by 14 channels of respiratory sound data of a single respiration cycle. Two reference libraries, pathological and healthy, were built based on multi-channel respiratory sound data for each channel and for each respiration phase, inspiration and expiration, separately. A multi-channel classification algorithm using K nearest neighbor (k-NN) classification method was designed. Performances of the two classifiers using spectral feature set corresponding to quantile frequencies and 6th order AR model coefficients on inspiration and expiration phases are compared.**

Keywords—**multi-channel respiratory sound data, k-NN classifiers, AR parameters, percentile frequencies, classification.**

I. Introduction

Auscultation of pulmonary sounds using a stethoscope is a simple, cheap and patient-friendly method which is widely used. However, it is regarded as a tool of low diagnostic value due to its subjectivity in evaluating pulmonary sounds, resulting in a large inter subject and intra subject variability and due to its inability to reproduce these findings for comparative assessment since lung sounds show variations, both among different subjects depending on the physiology (age, sex, type and degree of illness etc.) and within an individual, depending on the localization of the auscultation place. Moreover, the stethoscope attenuates frequency components above 120 Hz, in spite of the fact that the respiratory sounds are known to include frequencies up to 2000 Hz and human ear is not very sensitive to frequencies below 120 Hz [1]. Based on the shortcomings of the method, there has been increased research activity for developing computerized methods for auscultation and diagnosis based on respiratory sounds [2-4].

The variations occurring in the characteristics of respiratory sounds heard over the chest wall provide the experienced physician important information about the pathological situation [5]. Respiratory sounds are classified roughly into two classes, breath sounds and adventitious sounds. Breath sounds are described as the normal respiratory noise heard on the chest wall and mouth. These are synchronous with the flow of air through the airways. In healthy lungs, breath sounds have a frequency range of 200-600 Hz. Adventitious sounds are additional respiratory sounds superimposed on normal breath sounds and can be discontinuous (crackles) or continuous (wheeze). Crackles are explosive, transient in character and can be classified as fine (higher pitch) or coarse (lower pitch). As a general rule, their duration is less then 20 ms, with a wide frequency range (100 to 2000 Hz). Wheeze is a sinusoidal waveform with duration of more than 100 ms. The presence of adventitious sounds usually indicates a pulmonary disorder. The type of the adventitious sounds, the number of occurrence per one breath and their location within the flow cycle give valuable information about the type and severity of the disease.

Recently, there have been studies [6-8] for the classification of respiratory sounds with a view to parameterize these sounds and to make auscultation a more objective and valuable diagnosis tool. In these studies, however, only sound data from one microphone was used in classification and the placement of the microphone on the chest was guided under the supervision of a pulmonary physician such that the microphone was placed on the location where the sound characteristics of the pathological subject varied the most from healthy sound data. In this study, parallel recording from 14 microphones placed on the posterior chest were used to extract two different sets of features for classification. Moreover, since due to the physiology of the lungs, the transmission characteristics and therefore the spectral characteristics differ for respiratory sounds heard at different locations on the chest, separate reference libraries were built for each microphone location both for healthy and pathological data corresponding to inspiration and expiration.

Our main interest is to compare two different feature sets derived from respiratory sounds for optimum classification where multi-channel classification algorithm with each channel weighted equally is used. Two class recognition problem made of healthy and pathological sound data is addressed. The performance of our classifier is based on how well it differentiates between healthy and pathological sounds.

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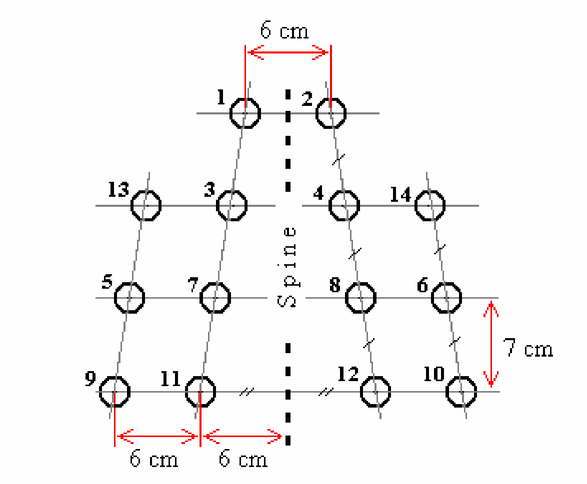

Fig.1. Microphone locations on the posterior chest

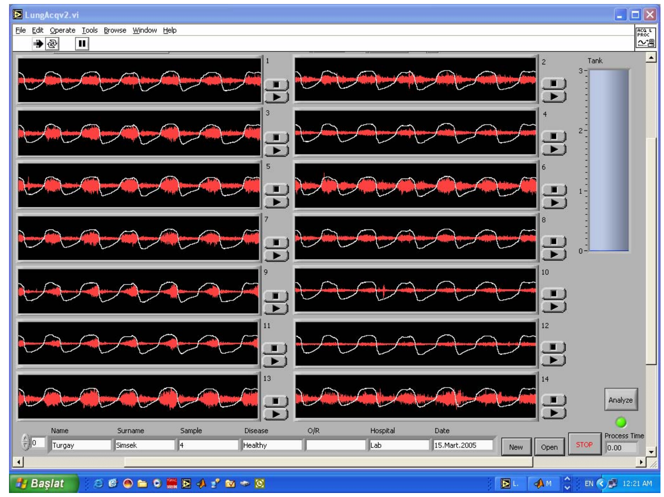

Fig.2. Simultaneously recorded flow and respiratory sound data using 14 microphones and a flowmeter

II. METHODOLOGY

A. Data Acquisition Method

To record the respiratory sound signals, a multi-channel recording system with 14 channels of sound acquisition and one channel of air-flow measurement has been developed. [9]. The sound signals were captured via 14 air-coupled electret microphones (Sony-ECM 44) placed on the posterior chest, with the simultaneous measurement of the air flow using a Fleisch-type flowmeter (Validyne CD 379) for synchronization on the inspiration-expiration cycle. Fourteen channels of sound signal were amplified, band-pass filtered between 80-2000 Hz to minimize frictional noise and heart sound interference and to prevent aliasing and digitized by a 12-bit ADC Card (Nİ-DAQ500) at a 9600 Hz sampling rate to be processed on PC, while flow signal was only low-pass filtered before digitization. Microphone locations are depicted in Fig. 1 and recordings from 14 microphones are depicted in Fig. 2.

In this study, healthy and pathological subjects were used to record 14 channels of sound data. Informed consent was obtained from the subjects before the recording experiment. The healthy subjects were all nonsmoking adults. Pathological respiration cycles were selected from subjects consisting of both restrictive and obstructive pulmonary diseases and the pathological lung sounds were heard all over the chest area. The recorded sound signals were automatically labeled as inspiration and expiration phases using the corresponding flow signal. The size of the segments for short-time analysis was chosen to be 256 samples as the respiratory sounds were assumed to be stationary in this interval. Consecutive frames had 25% of overlap. All of the sliding frames were weighted by a Hamming window to reduce the spectral leakage. Thus our sample space consisted of 256- sample segments of various respiration cycles.

B. Feature Selection and Classification Algorithm

Two different feature sets derived from 14 channels of sound data separately for inspiration and expiration cycles were used in the classification experiments. A multi-channel k-NN classifier with Euclidian distance metric measure was designed.

The first feature set consisted of autoregressive (AR) model coefficients. An autoregressive signal model was assumed for the respiratory sounds. It has been shown in various studies that such a model is suitable for representing lung sound signal [6,7]. AR parameters were derived for each segment of the respiratory sounds, where

$$s_f^{(m)}(n)=\sum_{k=1}^{p} a^{(m)}(k,f)\, s_f^{(m)}(n-k)+e_f^{(m)}(n),\; n=1,2,\ldots,N$$

where m denotes the segment index, N is the segment size, f labels the inspiration- expiration phases, and $a^{(m)}$ (k,f) is the kth AR coefficient. The model order p was chosen 6 to establish best order for classification. The second feature set used consisted of percentile frequencies. The frequency spectra of all segments were calculated for each channel for inspiration and expiration cycles separately and the average of these spectra were taken. From the averaged spectra, the percentile frequencies, namely f25, f50, f75 and f90 were calculated. These percentile frequencies are the frequency points which correspond to the 25%, 50%, 75%, and 90 % of the total area under the power spectrum density curve. Each channel for each person was represented by one feature vector formed by f25, f50, f75 and f90 as opposed to the AR feature set where each channel was represented by a number of vectors corresponding to the 6 AR coefficients of each 256-sample segment.

K-NN classifier was chosen for the classification experiment. In the k-NN classification method, the unknown feature vector is classified as belonging to the ith class, if a measure of the distance to its k nearest neighbor in that class is smaller than that of the other class. Euclidean distance metric was used with the classifier and the percentile feature vectors were normalized to equalize the effect of all frequencies before they were inputted to the classifier. Classifiers were trained separately for each channel using the feature space belonging to that channel. Leave-one-out method was employed in performance measurements. This method is said to provide good estimates of probability of error in case of small sample populations. In this method, the classifier is trained using all samples except the one to be classified, and then the removed subject is classified. In the k-NN classifier, k was chosen to be 3 in this study.

Each channel of a person is classified by the k-NN classifier. In the feature set corresponding to AR coefficients, decision for a channel is made by majority voting of all segments belonging to data obtained from that channel. In the percentile frequency feature space, however, each channel is represented by one averaged vector of percentile frequencies corresponding to the spectra of inspiration and expiration, respectively. After the decisions for all channels are reached, the final decision for the subject is made by using majority voting among channels. So the contribution of each channel to the final decision is equal. The block diagram of the classification scheme for different feature spaces are given in Fig. 3 and Fig. 4, respectively.

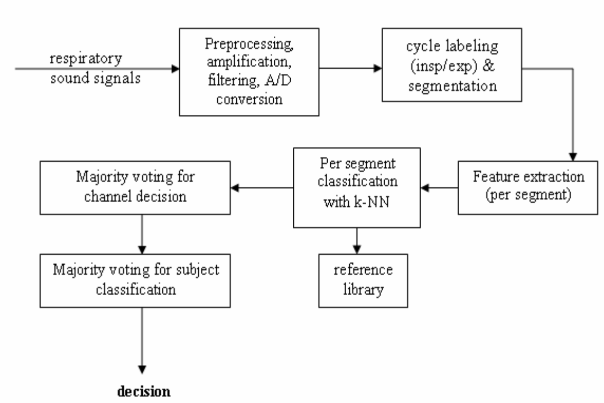

Fig.3. The block diagram of the classification algorithm for AR parameter vector space

III. Results and Discussion

In this study, the classification experiment was carried out on the data base consisting of 14 channels of respiratory sounds from 27 healthy and 21 pathological subjects. The pathological subjects consisted of 10 male and 11 female subjects, thirteen of whom had restrictive pulmonary disorder and eight of whom had obstructive pulmonary disorder. The pathological sound data was recorded from Yedikule Pulmonary Disease Hospital in Istanbul. Performance of classifiers was measured by means of the following statistical parameters:

Sensitivity: number of pathological subjects classified correctly / total number of pathological subjects;

Specificity: number of healthy subjects classified correctly /total number of healthy subjects;

Accuracy: number of subjects correctly classified / total number of subjects.

The performance of the classifier with different feature spaces is summarized in Fig. 5. Maximum accuracy of

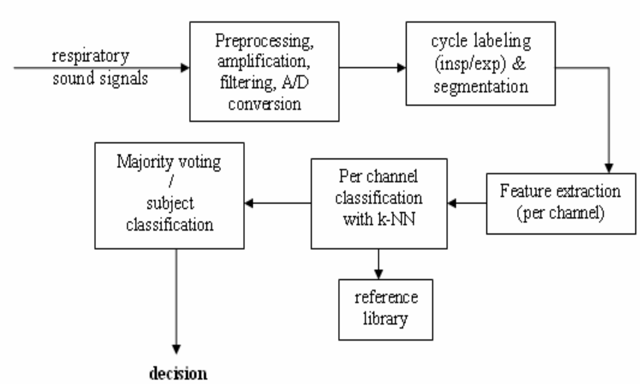

Fig.4. The block diagram of the classification algorithm for percentile frequency vector space

77.8 % of correct classification is achieved using AR parameters in expiration whereas this figure falls to 68.9 % for inspiration. With percentile frequencies, higher correct classification is obtained in inspiration with a figure of 72.7 % whereas the figure falls to 70.5 % for expiration. In general specificity figures are better for expiration. In percentile frequency feature space, sensitivity and accuracy figures are better for inspiration whereas for AR vector space, sensitivity, specificity and accuracy are all better for expiration.

IV. CONCLUSIONS

In this study, a multi-channel k-NN classification method using two different modeling approaches, AR and power spectral analysis, were compared in the classification of respiratory sounds as healthy and pathological. The sound signal was analyzed in two phases as inspiration and expiration separately due to the nonstationarity of the signal, and classification was performed separately for each phase.

In a further study, reference libraries corresponding to subphases, e.g., early, mid, late inspiration / expiration will be used in classification. Pathological sound signals will be further classified into specific diseases. In this study, the contribution of each channel to the final decision was taken as equal however the impact of each channel and microphone location on final decision will be further studied and be taken into consideration, attaching different weights to different channels.

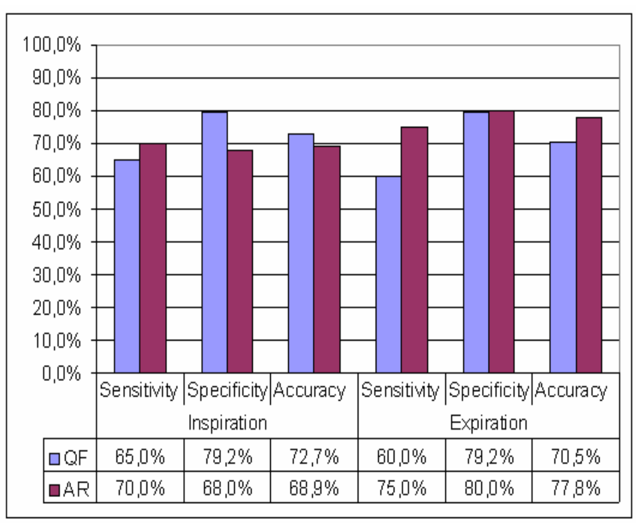

Fig.5. Performance of the k-NN classifier using AR parameters and percentile frequencies. QF stands for percentile (quantile) frequencies

There is a great amount of information in lung sounds that are not evaluated or assessed by physicians. Computerized analysis can be used as an aid in the diagnosis. Moreover lung sounds provide regional information, which can be accessed more easily through a multi-channel acquisition system. This parallel lung sound recording approach also decreases the time for auscultation of 14 different locations, making it a more efficient tool.

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