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Classifying Respiratory Sounds with Different Feature Sets

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Abstract—**In this study, different feature sets are used in conjunction with k-NN and artificial neural network (ANN) classifiers to address the classification problem of respiratory sound signals. A comparison is made between the performances of k-NN and ANN classifiers with different feature sets derived from respiratory sound data acquired from one microphone placed on the posterior chest area. Each subject is represented by a single respiration cycle divided into sixty segments from which three different feature sets consisting of 6th order AR model coefficients, wavelet coefficients and crackle parameters in addition to AR model coefficients are extracted. Classification experiments are carried out on inspiration and expiration phases separately. The two class recognition problem between healthy and pathological subjects is addressed.**

Keywords—**k-NN classifiers, ANN classifiers, AR parameters, crackle parameters, wavelet coefficients, respiratory sounds, classification.**

I. Introduction

Chest auscultation via a stethoscope is a widely used, patient-friendly and inexpensive method for the evaluation of the pulmonary diseases, however it is considered to be of low diagnostic value due to its inherent subjectivity. Moreover the stethoscope attenuates frequencies above 120 Hz below which the human ear is not very sensitive to and lung sounds contain frequency components up to 2000 Hz [1]. In recent years, much research has been carried out on computerized methods of digital recording and analysis of respiratory sounds with a view to make pulmonary sounds a valuable source of information for diagnosis [1-3]. The spectral characteristics of pulmonary sounds show variations according to the state and pathology of the lung. The spectra of the pathological sounds contain higher frequency components due to the changes in the transmission characteristics of the lung. Moreover in the case of pathological subjects, lung sounds contain adventitious sounds which are either continuous (e.g. wheezes) or transient (e.g. crackles) in behavior [4]. The physician usually recognizes these adventitious sounds and uses the information regarding the presence of crackles and their characteristics (number, epochs of occurrence and pitch) in order to arrive at a diagnosis. Although crackles are indicative of different diseases, duration of crackles is usually less than 100 ms so that they have insignificant influence on the total spectrum. Therefore, their contribution in the spectral analysis of respiratory sounds is minimal.

In recent years, several studies have been conducted on pulmonary sounds for their parametric representations with the final aim of building a computerized diagnostic tool to aid the physician. In previous studies carried out in our laboratory, various classification algorithms utilizing lung sounds have been investigated and feature spaces using AR parameters have been utilized in these classifiers [5]. In this study, feature spaces consisting of AR model coefficients along with crackle parameters and wavelet coefficients have been built and used with k-NN and ANN classifiers and their performances have been compared.

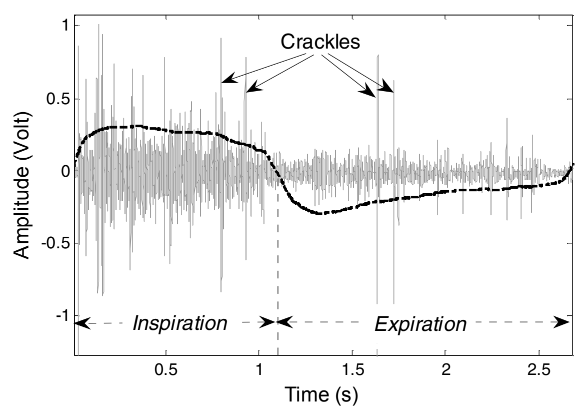

Fig.1. Simultaneously recorded flow and pathological respiratory sound data containing crackles

II. Methodology

A. Data Acquisition Method

An air-coupled electret microphone (Sony-ECM 44) placed on the posterior basilar of the subject is used to record respiratory sounds and airflow is recorded using Fleisch-type flowmeter (Validyne CD379) to synchronize on the inspiration-expiration phases. The placement of the microphone is guided by the physician so as to best represent the auscultated sound. The subjects are monitored to breathe at the flow rates above 1 L/s for optimum lung sound intensity. A low-noise preamplifier and a band-pass filter with flat frequency response at 80-2000Hz are used in order to minimize frictional noise and heart sound interference and for an anti-aliasing cut-off frequency of 2 kHz [6]. The high-pass section of the filter is a sixth order Bessel filter for minimum phase distortion and the low-pass

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section of the filter is an eighth order Butterworth filter. The amplified signals are digitized by a 12-bit ADC Card (NI-DAQ500) at a 5 kHz sampling rate and stored. A sample of the recorded data from a pathological lung containing crackles may be depicted in Figure 1.

B. Feature Selection

In this study, data of 20 healthy and 20 pathological subjects are used for the classification experiment. The pathological subjects consists of 10 male and 10 female respiratory disease patients, twelve of whom have obstructive pulmonary disorder and eight of whom have restrictive pulmonary disorder. Their average age is 59.8 ± 14.2. One randomly chosen respiratory cycle represents each subject.

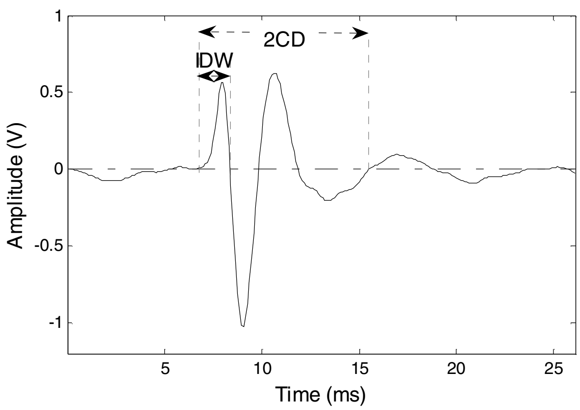


Fig.2. The initial deflection width (IDW) and two cycle duration (2CD) of a crackle.

Three different feature sets have been built from the data set consisting of healthy and pathological respiratory sounds. Separate feature sets are built for the inspiration and expiration phases since classification experiments are carried separately on these phases. The first feature set consists of AR model coefficients. Sixth order AR model coefficients are extracted from respiratory sounds to form the feature set for the classifier as it was shown in [5,7,8] that such a model is adequate to represent respiratory data. Each phase is divided into thirty segments which overlap 25% and each segment is represented by a vector formed of six AR model coefficients. Since the number of segments is constant, the duration of each segment is approximately between 50-60 ms depending on the duration of the respiration cycle. The sixth order AR coefficients are calculated using Yule-Walker method. A second feature set is built from crackle parameters in addition to sixth order AR model coefficients. Crackles in each segment are extracted manually. The parameters used to represent the crackles are initial deflection width (IDW), two cycle duration (2CD) and volume of occurrence (VO). IDW is the duration of the first deflection of the crackle; 2CD is the duration of the first two cycles of the crackle. IDW and 2CD are depicted in Figure 2. VO is the ratio of the air volume at which the crackle occurred to the total volume inspired or expired and is related to the epoch of crackle occurrence. One additional feature contained in the feature vector is used to indicate the presence or absence of a crackle in the segment with a value of “1” or “-1”, respectively.

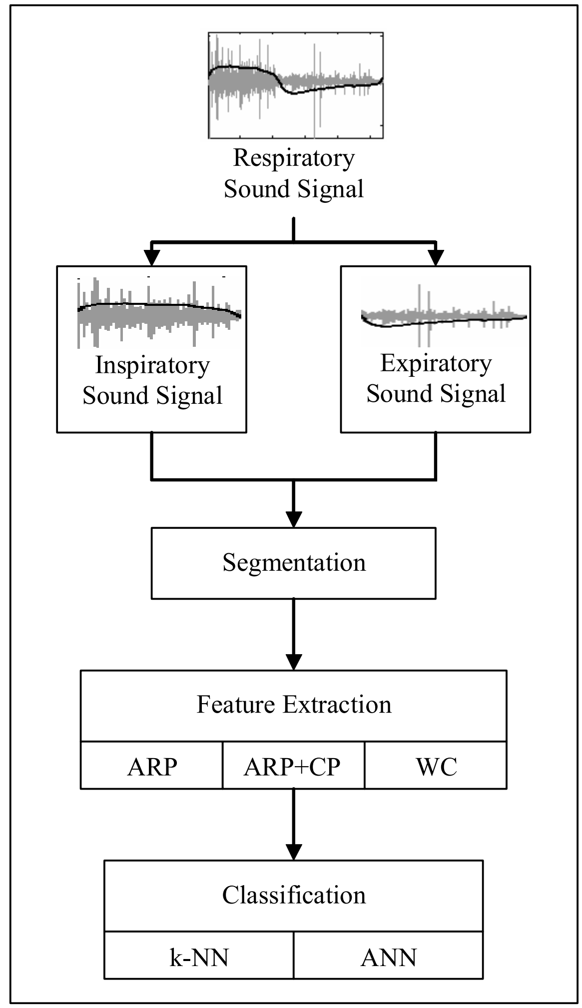


Fig.3. The flow chart of the classification algorithm.

The third feature set consists of parameters derived from wavelet transform of the respiratory sound signal which is decomposed into the frequency subbands using the 8th order Daubechies’ wavelet. Wavelet filters resembling respiratory crackles increase the correlation between short duration transients and the wavelet transforms, therefore, enhance their bearing on the decomposed signal component. Daubechies’ wavelets have been used in an earlier study in an earlier study in the detection of crackles due to their resemblance to crackles [9]. Four level decomposition is conducted to get a dyadic structure of five sub-spaces of the original signal representing the following five octaves: 2500-1250 Hz, 1250-625 Hz, 625-312.5 Hz, 312.5-156.25 Hz, 156.25-0 Hz. Then each level of decomposition is reconstructed and a fourth order AR model is used to represent reconstructed coefficient vector at each level. The parameters calculated by means of the Yule-Walker method constitute the four features of the vector and the fifth vector is a volume constant corresponding to the fraction of tidal volume of the corresponding sound segment.

C. Classification

Two different classifiers are used, namely, k-NN and ANN classifiers. In the k-NN classification methods, the unknown segment is classified as belonging to the ith class, if the majority of its k nearest neighbors belongs to that class. In this study, Euclidean distance and two values of k, 5 and 9, are used. In ANN classification, a feed-forward back-propagation network with three layers, namely, one input, one output and one hidden layer, is used. The performance and activation functions of the network are the mean-squared error and hyperbolic tangent sigmoid function, respectively. Levenberg-Marquardt learning algorithm is utilized to train the networks. Leave-one-out method is applied for performance measurements where the classifier feature space is built using all subjects except the one which is classified. The procedure is repeated until all subjects are classified individually. Classification experiments are carried out on inspiration and expiration phases separately and final decision for each inspiration or expiration cycle is reached using majority voting of all segment decisions for a subject.

III. Results And Discussions

In this study, the database consists of respiratory sounds from 20 healthy and 20 pathological subjects. The pathological sound data is recorded in the pulmonary clinic of the Cerrahpasa Medical School of Istanbul University. Performance of classifiers is 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.

Performance of the k-NN classifier for two values of k, namely, k=5 and k=9, is summarized in Figure 4. When 6th order AR coefficients are used as feature vectors, the accuracy of the classifier for the inspiration phase is 75% and 65% for k=5 and k=9, respectively. For expiration, the accuracy of the classifier is 82.5% and 77.5% for k=5 and k=9, respectively. The accuracy of the classifier improves considerably when crackle parameters are added to the feature vectors, reaching 90% each for inspiration for both k=5 and k=9, and 90% and 92.5% for expiration for k=5 and k=9, respectively.

Similarly, considerable improvement is obtained for sensitivity and specificity figures with the addition of crackle parameters to the feature vectors. Performance of the ANN classifier acting on the AR feature set and AR + crackle parameter feature set is summarized in Figure 5.

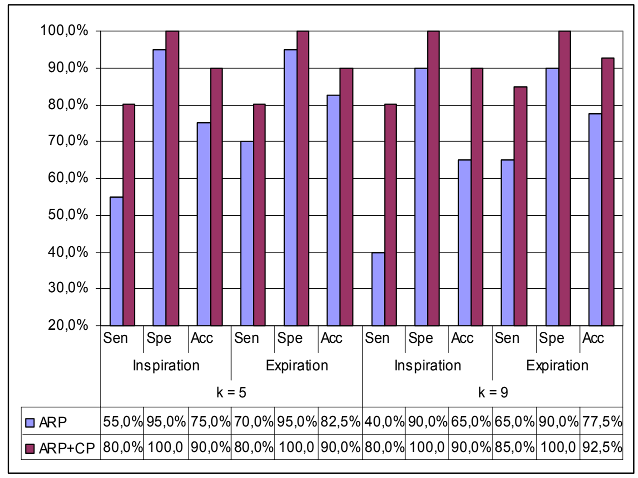


Fig.4. Performance of the k-NN classifier for k=5 and k=9 using AR parameters (ARP) and AR + crackle parameters(ARP+CP). *Sen* is sensitivity, *Spe* is specificity, *Acc* is accuracy of the classifier.

Using six AR model parameters, 80% is obtained for the inspiration phase for accuracy, sensitivity and specificity. As for the results of the classifier of the expiration cycle, 87.5% for accuracy, 85% for specificity and 90% for sensitivity is achieved. Including crackle parameters in the feature vector enhances the performance of the classifier significantly, achieving 92.5% accuracy, 90% specificity, 95% sensitivity for inspiration and 92.5% accuracy, 95% specificity, 90% sensitivity for expiration.

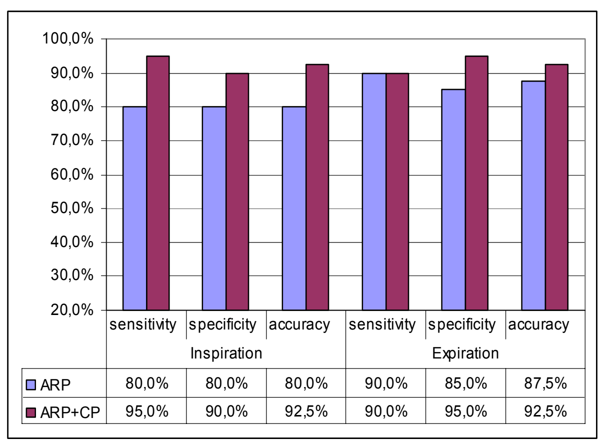
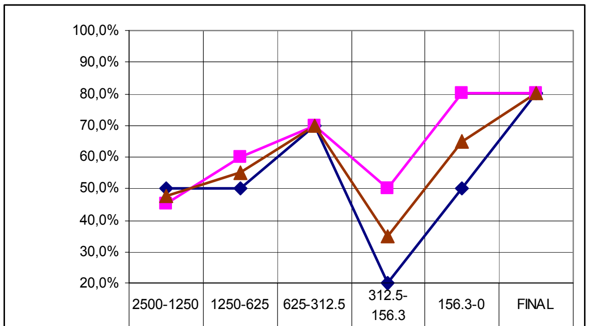


Fig.5. Performance of the ANN classifier using AR parameters (ARP) and AR + crackle parameters (ARP+CP). *Sen* is sensitivity, *Spe* is specificity, *Acc* is accuracy of the classifier.

The third feature set consisting of wavelet coefficient based feature vectors is used with an ANN classifier with five input nodes, five hidden layer nodes and one output node. Because of the type of the activation function, network outputs for each segment range from -1 to 1.The sum of results from all segments, namely thirty segments in this case, conveys the result of each subject. Decisions are made according to the sign of the final sum from all segments from all octaves. The performance of the classifier acting on the expiration cycle is depicted in Figure 6. Although the results seem low for each octave, the total figure is relatively high for the final decision which is the sum of all output node values from all segments and all octave bands, reaching a value of 80% for accuracy, sensitivity and specificity.



	2500-1250	1250-625	625-312.5	312.5-156.3	156.3-0	FINAL
sensitivity	50,0%	50,0%	70,0%	20,0%	50,0%	80,0%
specificity	45,0%	60,0%	70,0%	50,0%	80,0%	80,0%
accuracy	47,5%	55,0%	70,0%	35,0%	65,0%	80,0%

Fig.6. Performance of the ANN classifier using wavelet transform based parameters for different subbands.

IV. Conclusions

In this study, classification of lung sounds from a microphone placed on the basilar chest is undertaken with a view to develop algorithms to help the physicians in the diagnosis of common chest diseases. The aim of the study is to compare the performances of two different classifiers, namely, k-NN and ANN classifiers, acting on different feature vector spaces. Two different values of k, namely k=5 and k=9, are used in the classification experiments. The classification is carried out on a two-class data space, i.e. between healthy and pathological subjects. The three feature vector spaces consist of 6^{th} order AR model coefficients, crackle parameters in addition to AR model coefficients and wavelet transform based parameters. It is observed that significant improvement is obtained with the addition of crackle parameters to the feature space in both classifiers. Crackles are important findings in the evaluation of respiratory sounds since their presence, epoch and pitch relate to various respiratory disorders. However, since they are short duration events, they have negligible bearing on the frequency spectrum and consequently are not well represented by autoregressive parameters. Therefore, combining AR parameters with crackle parameters is a promising method for the classification of respiratory sound signals. Similarly, wavelet transform based feature vectors give comparable results in ANN classifiers. The results also indicate the octave band where the healthy and pathological sound signals overlap most, resulting in poor performance, namely the 312.5-156.25 Hz frequency band. In conclusion, these approaches show promising results for the eventual computerized diagnosis system using respiratory sounds. The number of healthy and pathological subjects in the training set could be increased and classification between different chest diseases could be attempted.

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