Comparision of LPC Based Parametric Techniques for Respiratory Sounds Recognition

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***Abstract*—Respiratory sounds are widely adopted marker of several diseases associated with upper and lower respiratory systems and lungs. Hence, recognition of respiratory sounds is an important step in diagnosis of the several diseases. In this study, it is aimed to recognize normal and asthmatic respiratory sounds. To accomplish this aim, analysis and classification process of the sounds were performed. LPC-based parametric techniques namely Linear Predictive Coefficients (LPC), Linear Prediction Cepstral Coefficients (LPCC) and Weighted Linear Prediction Cepstral Coefficients (WLPCC) techniques were used in analysis and feature extraction process. Linear prediction coefficients, cepstral coefficients and weighted cepstral coefficients were evaluated as characteristic features of the sound signals. In addition, Fuzzy C Means (FCM) clustering algorithm was used to achieve feature reduction. k nearest neighbor (kNN) and fuzzy k nearest neighbor (F-kNN) classifiers were design to classify respiratory sounds as normal and asthmatic sound signals. As a result of this study, the LPC-based parametric techniques were compared in terms of the effect on classification.**

***Index Terms*—linear predictive coefficients, linear prediction cepstral coefficients, weighted linear prediction cepstral coefficients, fuzzy C means, k nearest neighbor, fuzzy k nearest neighbor.**

I. Introduction

Respiratory sounds produced by the movement of air on the bronchial tree [1] are heard differently than normal when there is any disease in the lungs and airways. Respiratory sounds heard as wheezes in patients such as asthma and chronic obstructive pulmonary disease (COPD) [2]. Also these sounds often occur as crackles in patients with cardiorespiratory and infectious disorders [3]. Based on these findings, it can be said that distinguish and recognize normal and abnormal respiratory sounds is an important step for diagnosing of several diseases associated with airways, upper and lower respiratory systems and lungs. Traditionally, physicians listen the sounds through stethoscope. They recognize type of sounds by interpreting them and then they decide whether there is any disease or not. However, in last decades, diagnosing of various diseases has gone beyond the clinical environment and it has begun to be made in the digital environment.

In the digital environment, diagnosis from the respiratory sounds contains recording the patient's respiratory sounds by an electronic device, followed by analysis of respiratory sound signals with signal processing techniques and classification of respiratory sounds for recognition of their types as normal and abnormal [4]. In this context, there have been several studies. Many of these studies have adopted parametric representation of these sounds [5]-[8]. These studies demonstrate that when the sounds are represented as parametric features, diagnostic information by recognizing type of sounds can be obtained in an acceptable way. For the parametric representation of respiratory sounds, different techniques have been used such as autoregressive analysis (AR), Linear Predictive Coefficients (LPC) and Mel Frequency Cepstral Coefficients (MFCC) [6].

This study aims to recognize and classify respiratory sounds as normal and asthmatic abnormal sounds. In order to accomplish this aim, we have studied parametric representation of sounds using LPC and its derivatives LPCC and WLPCC techniques. After the parametric features extracted by these techniques were reduced to smaller size with Fuzzy C Means (FCM) clustering algorithm, they were used as inputs to the k Nearest Neighbor (kNN) and Fuzzy K nearest neighbor (F-kNN) classifiers. These classifiers were then used as a tool for the automatic classification of the normal and asthmatic abnormal respiratory sounds. Thus, this study constituted an important step for the diagnosis of asthma disease.

II. Materials and Method

In this study, respiratory sound signals were passed through 4 stages; preprocessing, feature extraction, dimension reduction and classification. After the sound signals were pre-processed with filtering and segmentation in the first stage, they were subjected to analysis by the LPC, LPCC and WLPCC methods. As a result of analysis, feature vectors were obtained as Prediction Coefficients (LPC parameters), Cepstral Coefficients (LPCC Parameters) and Weighted Cepstral Coefficients (WLPCC Parameters). Dimension of the obtained feature vectors is too high. High dimensionality

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makes pattern recognition problem difficult. Also classification process conducted with feature vectors takes a long time and effective classification results may not achieved. Therefore, before the feature vector is applied to a classifier, feature reduction should be performed. For this reason, followed the feature extraction stage, feature reduction is realized by performing Fuzzy C Means (FCM) clustering algorithm. In the last stage, classifiers were used to classify the reduced features to two distinct classes namely normal and asthmatic. . For testing the reliability of the analysis results, 2 different classification algorithms; k-Nearest Neighbor (kNN) and fuzzy k-Nearest Neighbor (f-kNN) algorithms were used. Classification process was carried out separately for right basal inhalation sounds, right basal exhalation sounds, left basal inhalation sounds and left basal exhalation sounds. As a result of the last stage, analysis methods LPC, LPCC and WPCC were compared according to classification accuracies.

Fig. 1 illustrates a block diagram of this study.

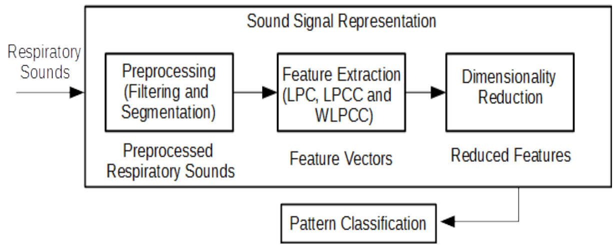

Figure 1. Block diagram of study.

A. Used Respiratory Sound Data

Harman recorded the respiratory sounds from right and left basal of chest for her study [9]. To prevent sounds coming from ambient, her sound recording process was carried out in the laboratories of the College of Medicine at University of Gaziantep. Researcher used Sony ECM T150 microphone with an air capsule to record sounds [9]. The sounds also were used in different studies [10], [11]. The sounds recorded by the researcher have also been used in this study. Normal respiratory sounds of 5 healthy people and asthmatic respiratory sounds of 5 patients were selected for our study. Each people have 2 respiratory sounds as a sound of right basal and a sound of left basal. The duration of these sounds varies between 10 and 14 second and sampling frequency of them is 8kHz. Sounds include more than one and different numbers respiration cycles.

B. Pre-Processing

According to literature studies [4], [9], [3], respiratory sounds don't contain considerable components in the low frequencies below 100Hz and high frequencies above 2000Hz. Especially, heart sounds are located between 20 and 100 Hz and they can introduce perturbations during the analysis of respiratory sounds [12]. In accordance with this information, it can be said that irrelevant frequency components do not provide useful information about the respiratory sounds and they should be filtered. Therefore, in the pre-processing stage of this study, the respiratory sound signals were filtered with high pass filter at 100 Hz (to eliminate muscle sounds, heart sounds and frictional noise), and low pass filter at 2000 Hz (to avoid aliasing). Due to the widespread use of Bessel and Butterworth filters [13], [14], 6th order Bessel high pass filter and 8th order Butterworth low pass filter were used in this study.

After the filtering process, each sound signal was segmented into a small duration of one complete cycle of respiration. And then every cycle was separated as inhalation and exhalation sound signals according to the start and end times of inhalation and exhalation phases. At the end of the segmentation process, it has been seen that duration of the every inhalation and exhalation sound segments is approximately 1 sec. Every 1 second-sound segment was evaluated and processed as a separate pattern. The feature extraction and classification operations that will be mentioned in the following sections are applied to each sound segment separately.

Table I shows the amount of segments (1 seconds-sounds) obtained at the end of the pre-processing stage.

TABLE I. AMOUNT OF SEGMENTS OBTAINED AT THE END OF THE PRE-PROCESSING STAGE

Respiratory Sounds		Normal (Healty)	Abnormal (Asthmatic)	Total
Right Basal	İnhalation	24	24	48
	Exhalation	23	27	50
Left Basal	İnhalation	25	22	47
	Exhalation	24	24	48

C. Feature Extraction Methods

1) Linear Predictive Coefficients (LPC)

LPC technique and its derivations LPCC and WLPCC are widely used in signal processing and especially in echoes, speech and musical sound processing applications [15]. These techniques are the parametric analysis techniques. They models the signal as output of the all-pole filter.

In the LPC technique, if a sound signal sample is given at time n (s[n]), this sample can be expressed as a linear combination of the past p samples of the sound signals [16]. Equation 1 explains fundamental idea of LPC.

$$s[n] = a_1 s[n-1] + a_2 s[n-2] + \ldots + a_p s[n-p] \qquad (1)$$

a1, a2,…,ap are the prediction coefficients. Also they can be called parameters. The number of the parameters is determined by the degree of the LPC method. In equation 1, p defines LPC degree in other words number of LPC parameters. Generally, estimation of the LPC parameters is carried out by two methods. These are covariance and autocorrelation methods. According to the study [17], although filter is designed with autocorrelation parameters is stable, this guarantee cannot be given for filters designed with covariance parameters [17]. Moreover, autocorrelation method requires less calculation than covariance [18]. Therefore this technique has been preferred for parameter estimation in most of the studies.

The LPC technique for any sound signal can be interpreted as shown in Fig. 1. Sound signals are one of the non-stationary signals. That's why analysis and evaluation of these sounds are difficult. In the LPC technique, with a framing process, non-static sound signals are split into to parts with smaller durations. In this way, small-duration signals become more stable. Because of the framing process, signal discontinuity may occur at the beginning and end of the frames. Generally windows are used to overcome discontinuity problems. After the windowing process, LPC parameters were estimated for small-duration signal (every frame) by using the Autocorrelation Levinson Durbin method. Estimated LPC parameters represent the signal. For this reason, generally, they are estimated for the signal and they are used as features of the signal.

Fig. 2 shows the calculation process of LPC parameters.

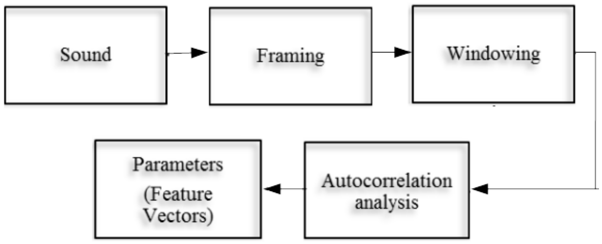

Figure 2. Calculation process of LPC parameters.

2) Linear Predictive Cepstral Coefficients (LPCC)

Cepstrum is defined as inverse Fourier transform function of the logarithmic Fourier. Based on this definition, it can be said that LPCC are the coefficients of the Fourier transform representation of the log magnitude spectrum [16]. While Cepstrum coefficients can be obtained by Fourier transform, they also calculated based on the linear prediction parameters [19]. That's way cepstral coefficients are referred as the Linear Prediction Cepstral Coefficients (LPCC). Rabiner and Juang [20] prove that LPCC more robust and reliable compared to LPC.

LPCC parameters are computed from LPC parameter as shown in Equation 2. p is referred as degree of technique as in Equation 1.

$$LPCC(p) = LPC(p) + \sum_{k=1}^{p-1}\left(\frac{k-p}{p}\right)LPCC(p-k)LPC(k) \quad (2)$$

3) Weighted Linear Predictive Cepstral Coefficients (WLPCC)

LPCC values provide more reliable and robust representation of sound signals when they are compared to LPC. However, the low-order Cepstral coefficients are sensitive to overall spectral slope and the high-order cepstral coefficients are sensitive to noise and other forms of noise like variability [21]. Weighting operation can be overcome these sensitivities. Weighting the cepstral coefficients minimize noise and also it eliminates major differences between Cepstral values.

Weighting the LPCC values can be easily achieved by using following equations namely Equation 3 and Equation 4 [21].

$$w_m = [1 + \frac{p}{2}\sin(\frac{\pi m}{p})], \qquad 1 \le m \le p \quad (3)$$

$$WLPCC(m) = w_m LPCC(m) \quad (4)$$

4) Fuzzy C Means (FCM)

Fuzzy C-Means (FCM) is a well-known unsupervised partitional clustering algorithm. Fuzzy C Means clustering algorithm was introduced by Dunn in the 1970s and this algorithm was developed by Bezdek in 1980s [22].

According to this algorithm, a pattern can belongs to more than one cluster with the fuzzy membership values which grades between 0 and 1 [23]. The FCM is based on minimization of an objective function. The algorithm starts with selecting the number of clusters as defined in the problem and initializing the membership matrix U [24]. This matrix contains the membership value for all points for each cluster. In the next step, cluster centers are computed using the membership matrix U. Once the cluster centers have been computed, the membership matrix is recalculated. New computed membership matrix is compared old matrix and the change in membership matrix is computed. If this change is lower than a predefined threshold (ε), then the process is stopped, otherwise, new cluster centers are calculated and membership matrix are updated with respect to the new cluster centers [24]. The iteration continues till the change in the membership matrix is minimized [24].

5) Feature cxtraction of respiratory sounds

In this study, LPC and its derivations LPCC and WLPCC techniques were used for feature extraction of 1 second-sound segments. Firstly analysis of sounds was carried out by LPC and prediction parameters were obtained as features of sounds. Then LPCC and WLPCC parameters were computed from LPC parameters as features.

First stage of the LPC is the determination of LPC degree in other words how much LPC parameters were used. According to Markel [25], optimum order of the AR model has a strong correlation with the sound sampling rate and for sampling rates of Fs ∈ [6 − 18] kHz, the optimum order would be M = Fs(kHz) + γ where γ = 4, 5 . Because AR approach is closely related to LPC technique, Yadollahi *et al.* [26] used this formula to determine degree of LPC technique. For 10kHz signal, they determined LPC degree as 14. Based on these references, we determined LPC degree as 12 for respiratory sounds with 8kHz.

After the determination of LPC degree, number of the frames was selected as 50. Each of 1 second-sound segments were divided into 50 frames. Thus, every frame contained approximately 20 msec sounds. The hamming window was used to recover the signal discontinuity resulting from the framing operation. After the windowing process, 12 LPC parameters were estimated for every frame by using the Autocorrelation Levinson Durbin method.

As a result of the performed operations, 50 frames belonging to every 1 second-sound segments and 12 prediction coefficients (LPC parameters) belonging to every frame were obtained. In other words, 50 x 12 feature values were obtained from ever sound segment. Feature extraction process of respiratory sounds using LPC can be summarized as shown in Fig. 3.

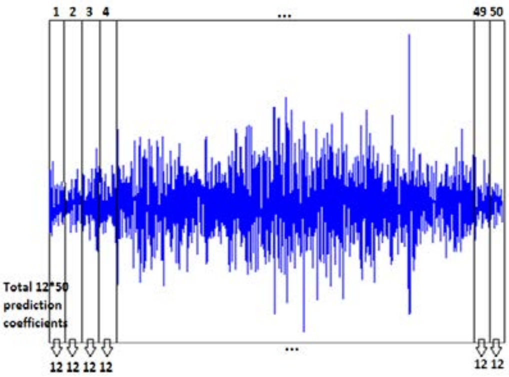

Figure 3. Feature extraction process of respiratory sounds using LPC.

For comparison purpose, LPC parameters found by the autocorrelation method were transformed into LPCC parameters. Afterwards, they were transformed into WLPCC parameters.

At the end of the feature extraction phase, feature vectors in dimension of 50 x 12 have been generated. This dimension is too high. That's why, classification process conducted with feature vectors takes a long time and effective classification results may not achieved. To avoid these negative situations, feature sizes must be reduced.

There are many size reduction techniques. Clustering process is one of the commonly used dimensionality reduction techniques. Dimensionality reduction can be performed using fewer features representing the clusters instead of using all the features. FCM clustering algorithm is one of the most commonly known and used clustering algorithms. In this study, FCM algorithm was selected for feature reduction.

In the performed study, 50 frames with 12 coefficients belonging to every sound segment separated into clusters using FCM algorithm. Instead of using all 50 frames belong to every sound segment; only frames forming the cluster centers were used. Cluster number was selected based on the SSE (sum of squared errors) criteria. SSE is most commonly used measure for evaluating the clustering. SSE is computed as in Equation 5.

$$SSE = \sum_{i=1}^{k} \sum_{p \in C_i} (p - m_i)^2 \tag{5}$$

where k is clusters, C is the set of objects in a cluster, m is the center point of a cluster. After the each iteration, SSE is checked. If SSE is decreasing, the number of iterations is increased. The iteration continues until the local minimum is reached. The number of iterations reached to the local minimum is determined as the number of clusters.

In this study, the number of clusters is determined as 6 by the SSE criteria for right basal inhalation and exhalation sounds. The number is determined as 7 by the SSE criteria for left basal inhalation and exhalation sounds. At the end of the clustering process, cluster centers with 12 coefficients were used as features of sounds.

When an exhalation sound of left basal is considered, Fig. 4 shows the clustering process in 2D plane.

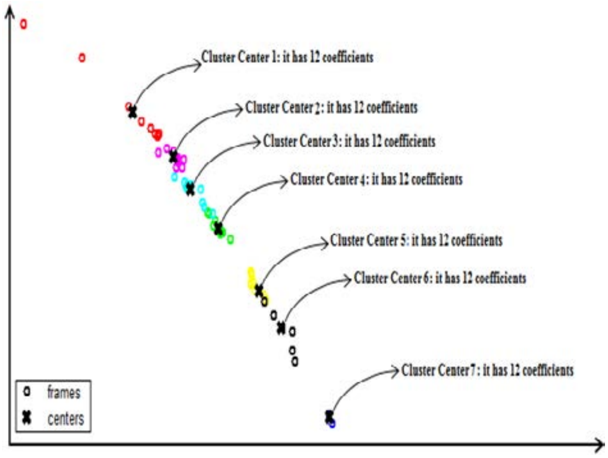

Figure 4. Clustering process for any sound segment of the left basal.

Reduced features for respiratory sounds are shown in Table II. As seen from the Table II, dimension of features is still not very small. To make it even smaller, we used statistical features of cluster center data such as max, min, standard deviation. However, these features could not fully represent the data and the success rate of classification was reduced. For this reason, we decided to use cluster centers with 12 coefficients instead of statistical features.

TABLE II. REDUCED FEATURES FOR RESPIRATORY SOUNDS

Respiratory Sounds		Number of Sound Segments	Number of Features for one segment	Cluster Number	Reduced Features
Right Basal	İnhalation	48	12*50 (600)	6	12*6 (72)
	Exhalation	50	12*50 (600)	6	12*6 (72)
Left Basal	İnhalation	47	12*50 (600)	7	12*7 (84)
	Exhalation	48	12*50 (600)	7	12*7 (84)

D. Classification of Respiratory Sounds

Classification process was carried out to determine respiratory sound type as normal and asthmatic. Classifiers applied to separately on the inhalation and exhalation sounds for both right basal and left basal.

K-NN algorithm is one of the commonly used supervised and nonparametric algorithms for classification. There is no training process in the kNN. Because of the this property, when it is compared to other classification techniques, kNN is a simple classification techniques with low computational cost and low calculation time [27]. The basic approach used for classification; it classify to desired pattern by looking k nearest neighbor. Unknown pattern is included to class of majority in these k neighbors.

Fuzzy k-nearest neighbor classifier (F-kNN) is an improvement of the standard KNN classifier. This classifier can improve performance of kNN especially in the biological and medical data classification problems. Unlike the standard kNN, F-kNN uses concepts from fuzzy logic to assign degree of membership to different classes while considering the distance of its k nearest neighbors [28]. Class of a pattern is determined as class which has the largest membership value. In this study, both kNN and F-kNN classification algorithms were used to classify respiratory sounds. k value was determined as 9 for two classifiers. Classification process was carried out with 1000 iterations and 10 cross-validations.

III. RESULTS AND DISCUSSIONS

Respiratory sounds are a biological signals providing information about the lungs, airways and respiratory system. Therefore, determining whether sounds are normal or different from normal (abnormal) is an important step for detection of pathological conditions of lungs, airways and respiratory system. In this study, it is intended to recognize normal and abnormal asthmatic respiratory sounds. To accomplish this intent, LPC, LPCC and WLPCC techniques were applied to each of the sound segments and this way sounds were analyzed. Prediction coefficients (parameters), cepstral coefficients and weighted cepstral coefficients were considered as features of the respiratory sounds.

kNN and F-kNN algorithms are commonly used for classification of biological sounds and they produce high performance. That's why, these algorithms were used to classify inhalation and exhalation sounds of right and left basal into two different types in this study. Classification accuracies obtained by kNN and F-kNN are shown in Table III.

TABLE III. CLASSIFICATION ACCURACIES OF TWO CLASS USING KNN

Feature Extraction Techniques		kNN Classification Accuracy (%)		F-kNN Classification Accuracy (%)	
		Inhalation	Exhalation	Inhalation	Exhalation
Right Basal	LPC	67.50	46.00	76.33	59
	LPCC	77.50	56.00	86.16	69.83
	WLPCC	**92.00**	**72.00**	**93.50**	**80.00**
Left Basal	LPC	58.50	65.50	73.00	74.6
	LPCC	66.00	73.50	88.50	81.50
	WLPCC	**81.00**	**79.50**	**92.00**	**89.00**

As seen from Table III, the accuracies obtained by WLPCC features are consistently higher than both LPC and LPCC. In the previous sections, it was explained that WLPCC are more robust than LPCC and LPC by applying the weighting function on LPCC. The weighting function is able to minimize the sensitivity of the low-order and high-order of LPCC to noise. Hence WLPCC provide better classification accuracy compare to LPCC and LPC. This finding is proven in this study. Conclusions of all the experimental results indicate that the WLPCC is better than LPCC and considerably outperforms LPC in all the experiments. Moreover, LPCC are highly outperformed than LPC due to the fact that LPCC have been shown to be more robust and reliable feature in sound classification than LPC.

The F-kNN classifier gave better results than kNN, using all of the feature extraction methods (LPC, LPCC, and WLPCC). The highest accuracy that obtained by WLPCC and F-kNN is 93.50%. This accuracy was obtained when right basal inhalation sounds were analyzed. When the kNN classifier and WLPCC method were used for the same sound, 92.00% classification accuracy was obtained. Both classification accuracies are quite high and very promising for diagnosis of asthma disease. According to results of current work, it can be said that breath disorder problems such as asthma can be effectively and successfully identified and detected by respiratory sounds, different feature sets and classifiers.

IV. CONCLUSIONS

Analysis of respiratory sounds is very important for the diagnosis of airway and lung diseases such as asthma. Many digital signal processing algorithms are used for analysis of heart sounds. Due to ease of use, less memory requirement and producing effective results, LPC, LPCC and WLPCC are most commonly used digital signal processing techniques for analyzing the sound signals.

In this study, normal and abnormal asthmatic respiratory sounds were analyzed using LPC, LPCC and WLPCC techniques. Prediction coefficients, cepstral coefficients and weighted cepstral coefficients obtained by these LPC based techniques were considered as characteristic features of the sounds. kNN and F-kNN algorithms were used to recognize two different respiratory sounds by classifying the reduced features. As a result of the classification process, it is observed that weighted cepstral coefficients represent the respiratory sounds better than prediction coefficients and cepstral coefficients. In other words, WLPCC technique extracts more useful features by analyzing them. Also we can say that analysis of respiratory sounds with WLPCC has high performance in the biomedical field. This analysis technique gives useful information about the pathological conditions of airways and lungs.

The results obtained from this study are very promising for defining different types of respiratory sound associated with various pathological conditions. Therefore, it can be said that detection of various pathological conditions is performed by analysis of respiratory sounds in a digital environment. However, more experimental work is required, especially with larger data sets in order to develop and commercialize real-time computer based sound analysis and disease diagnostic systems.

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