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Preliminary Recognition of Respiratory Deformities using Cepstral Analysis

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Abstract - **This paper proposes an efficient method to classify normal and abnormal respiratory sounds. Traditionally, abnormal breath sounds are detected using stethoscopes and qualitative methods based on a physician's own hearing. Computerized methods of respiratory sound analysis will provide a quantitative basis for abnormal respiratory sound detection. The respiratory sounds are analyzed by the Mel Frequency Cepstral coefficients and classified by SVM Classifier . Here, Gaussian Mixture Model is used as the classifier in conjunction with the wavelet derived features. The pre-recorded breath sounds from R.A.L.E. Repository is used for analysis and the results obtained are found to be satisfactory. An SVM based system, trained using the MFCC Features, and was implemented to classify the lung sounds in to different classes as normal, wheeze, stridor and rhonchi.**

Keywords* - *Respiratory sounds, Gaussian Mixture Model, Wavelet transform, statistical features- mean standard deviation, kurtosis, skewness.

I. INTRODUCTION

Respiratory sounds are created in the large airways where air velocity and turbulence compose vibrations in the airway walls during the process of breathing. These vibrations are then sending out through the lung tissue and thoracic wall to the surface where they may perceive sound with the aid of a stethoscope, micro phone or any other sensors. Respiratory sounds can be classified into two categories, either normal or Pathological.

Nowadays, asthma is becoming a common disease that may occur at any age and have become a public health challenge to the world today [1]. It is a chronic inflammatory diseases of the respiratory airway and can be hyper- responsiveness to a variety of stimuli [2]. The asthmatic patient suffers attacks such as coughing, dyspnea, and the main manifestation is wheezing [3]. Sounds generated during breathing can be a good source of information on lung's health [4]. Any characteristic changes of the normal lung sounds can imply a diseased condition that probably is invading the lung. Each type of disease is different from each other and the variation can be ascertained from sound characteristic, pitch, amplitude, frequency, duration, etc. [5]. With regard to asthma, symptoms originating from the wall oscillations of narrowed airways at critical flow rates causes wheeze to occur [3]. Auscultation of the chest via a stethoscope provides useful information to the physician for the diagnoses of respiratory disorders. However, due to the subjectivity in auditory perception among physicians, and variability in their verbal descriptions of sound characteristics, fuzzy and qualitative nature of the diagnosis has become the major problem for this rewarding method [6–8]. In the last three decades, on the other hand, technical advances in sound measurement and signal processing techniques have opened new avenues for the auscultation based diagnosis of pulmonary disorders [9–14]. Automatic recognition of respiratory sounds is useful in providing a computer-aided tool to auscultation and increases its potential diagnostic value [15]. There are two major difficulties in developing such a tool: (i) respiratory signals are non-stationary due to changes in lung volume and Low rate during a cycle. (ii) These sounds have a large inter-subject variability due to age, weight and physiology and considerable intra-subject differences due to the evolution state of pathology. Therefore the use of conventional classification algorithms prove inadequate, and novel approaches must take into account the problems of small sample size, diversity of sounds, and the cyclic behavior of signals

In lung medicine there is no universal pattern or parameters' threshold indicating the presence or absence of a pathology. Therefore, Zheng and coll. [16] propose to establish a personalized pattern, combining information coming from sounds and other measurement applied to the patient. They aimed at recognizing pattern of pulmonary sounds. The method applied can be divided into two stages: characterize the variables that can be extracted from the waveform of pulmonary sound, and the changing in these variables that will provide information concerning the pattern variations.

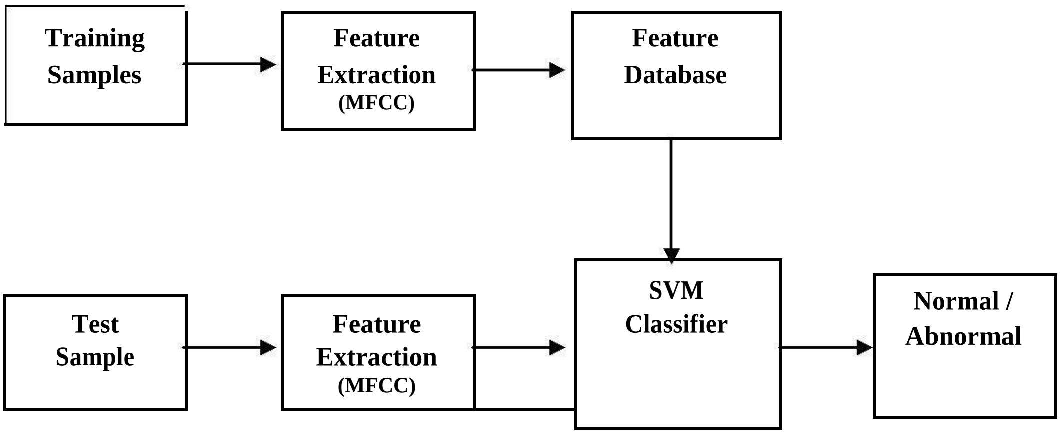


Figure 1: Respiratory signal Classification System

Guler and coll. [17] focus on artificial intelligence technics; they combined neural network and genetic algorithm for analysis of lung sounds. First, they selected complete respiratory cycles, on which a PSD (Power Spectrum Density) of 256 was applied. Then, a multilayer perceptron (MLP) neural network was employed in order to detect the presence or absence of adventitious sounds (wheezes and crackles). Each sound is associated to several characteristics and to a diagnosis. 129 specific characteristics were checked of (PSD0,…,PSD128). Afterwards, different learning rules were used in order to associate characteristics and diagnosis.

In [18], Kahya and coll. make a comparison between k-NN (k-nearest neighbour) and ANN (artifi cial neural networks). They use different features extracted from the respiratory signal; actually each cycle is divided into six segments with three features: autoregressive coefficient, wavelet coefficient and crackles' parameters. Moreover, the performance of the classifiers was measured with the following statistical parameters: sensitivity, specificity, accuracy.

Then, in [19], they added crackle parameters to the observed features in order to increase the performance of classification. It was observed that addition of crackles parameters to feature vectors and fusion of phase decisions improve classifi-cation results.

Cohen and Landsberg [20] realize classification of normal and adventitious sounds in two stages: linear prediction of coefficients, and features of the energetic envelope. Seven types of respiratory sound were thus classified, among which four normal sounds: vesicular breath sounds (V), bronchial breath sounds (B), broncho-vesicular breath sounds (BV), and tracheal breath sounds (T). The features extracted were: FFT, PDS estimation by means of linear prediction (LCP). Nevertheless, in this study, a manual decision of the inspiration/expiration periods was realized. The main objectives are: characterize quantitatively several respiratory sounds and provide an automatic classification method of these type of sounds. Finally, the diagnostic will be done by a physician, and based on the sound analysis associated with other diagnostic values.

Dokur and Olmez. [21] use wavelet transform. The best samples are selected by dynamic programming. Then a Grow and Learn neural network is used for classification. The process of decision is made up of three stages: process normalization, feature extraction, artificial neural network by classification.

The paper is structured as follows. The next section discusses the Proposed Method. The Section 3 gives the Classification Results. Finally, Section 4 gives the Discussion and Conclusion of the proposed method.

II.Respiratory Signal Classification System

The overall block diagram of the proposed feature extraction scheme is presented in Fig. 1.Te first step in the respiratory disease recognition system is to extract features i.e. identify the components of the respiratory signal that are good for identifying the characteristics of the respiratory sound. Among the variety of parametric representations of the sound are found in the literature, such as linear predictive coefficient

(LPC) and Mel- frequency cepstral coefficients (MFCC).

Respiratory Signal Classification system involves two phases, i.e., training and classification.

Mel Frequency Cepstral Coefficents (MFCCs)

Mel Frequency Cepstral Coefficents (MFCCs) are the widely used feature in automatic speech and speaker recognition. It combines the advantages of the cepstrum analysis with a perceptual frequency scale based on critical bands. The steps for computing the Mel-Frequency Cepstral Coefficients from the signal are as follows:Framing the Signal, Windowing, FFT, Mel- Frequency Warping and Computing the Cepstral Coefficients

Framing: The respiratory signal has to be short enough so that it can reasonably be assumed to be stationary, for extracting the parameters. Thus to model dynamic parameters, the signal is divided into successive frames. To avoid loss of information overlapping between frames is necessary. Framing is done with a frame size of 256 samples and overlap size of 100 samples.

Windowing: To minimize the distraction at the starting and at the end of the frame, windowing is [22]. It is done on each individual frame so as to taper the signal to zero at the beginning and at the end of frame. The Hamming window is used because it has a wide main lobe and small side lobes, making it a smooth lowpass filter with less leakage [23].

Hamming window w(n) has the form

—— (1)

where N represents the width, in samples, of a discrete-time window function. Typically it is an integer power-of-2, such as $2^{10} = 1024$. n is an integer, with values $0 \leq n \leq N\text{-}1$.

Fast Fourier Transform: FFT is used for converting the input signal from the time domain to the frequency domain. Fourier transformation is a fast algorithm to apply Discrete Fourier Transform (DFT), on the given set of Nm samples. After windowing the respiratory signal Fast Fourier Transform (FFT) is applied to each frame and its squared magnitude is calculated. For sampled vector data

Pre-emphasis: Preemphasis is used to boost the energy of high frequency signals. Thus preemphasis helps to equalize the spectral tilt in speech and the signal is spectrally flattened. The output of pre-emphasis [22] is related to input s(n) by

$$s(n)' = s(n) - \alpha\, s(n-1) \qquad (2)$$

where α is Preemphasis factor whose value varies from 0.9 to 1.

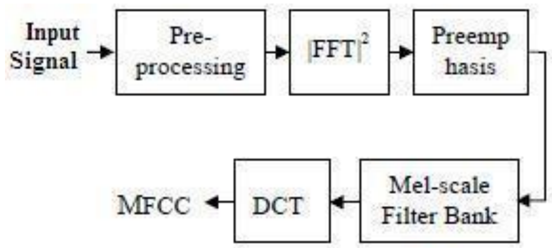


Figure 2: Mel – Cepstral Feature Analysis

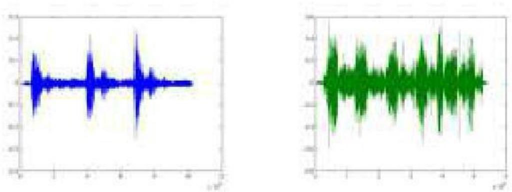
Mel Scale Filter Bank: Mel is the unit of pitch. Melscale is linear below 1 kHz and logarithmic above 1 kHz [24]. If triangular filters are used in filter bank, the correlation between a subband and adjacent subband is lost. In this paper Gaussian filters are used. The gaussian filters are chosen for many reasons. First, it is symmetric and high frequency components are involved. Second, gaussian shaped filters provide smooth transition from one subband to other preserving most of the correlation between them. The filters in the filter bank are arranged such that more number of filters are present in the low frequency range.

Discrete Cosine Transform: Discrete Cosine Transform (DCT) is applied to the log of the Mel Spectral Coefficients to obtain MFCCs. By applying DCT decorrelated coefficients are obtained. The zeroth coeffient has average log energy and hence it is discarded. In MFCC the frequency bands are logarithmically spaced. As the frequency bands are positioned logarithmically in MFCC it approximates the human response system more closely than any other system. These coefficients allow better processing of data.

SVM: Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. Supervised learning involves analyzing a given set of labelled observations (the training set) so as to predict the labels of unlabelled future data (the test set). Specifically, the goal is to learn some function that describes the relationship between observations and their labels [25]. More formally, a support vector machine constructs a hyper plane or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (so-called functional margin), in general the larger the functional margin the lower the generalization error of the classifier. In the case of support vector machines, a data point is viewed as a p-dimensional vector (a list of p numbers), and we want to know whether we can separate such points with a (p − 1)-dimensional hyper plane. This is called a linear classifier. There are many hyper planes that might classify the data. One reasonable choice as the best hyper plane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyper plane so that the distance from it to the nearest data point on each side is maximized.

IV Results and Discussion

The experimental results for the classification of abnormal lung sound from normal are shown in this section. Signals obtained from RALE Repository are used for analysis. Some of the sample signals are shown below.



(a) Normal **(b) Wheeze**

Figure 2: Sample Respiratory Signals

The input signals is splitted in to frames of length 256 and are used for further analysis. Feature vectors are obtained for MFCC features. For every frame of the respiratory signal 20 DCT coefficients are obtained and the first DCT coefficient is discarded (since it yields the DC value). As a result every frame of the speech signal contributes 19 MFCC coefficients.

From the available samples of respiratory signals, 66 % of it was used for training and remaining for testing. The confusion matrix can show us how many correct classification rates have been identified. In the Table1 and 2, True positive (TP) is the ratio between normal signal correctly classified and the total number of normal signal. False negative (FN) is the ratio between wrongly classified pathological signal and the total number of normal signal. True negative (TN) is the ratio between pathological signal correctly classified and the total number of the pathological signal. False positive (FP) is the ratio
between normal signal wrongly classified and the total number of pathological signal.

Table 1.The confusion matrix for Two Class Problem.

	Normal	Abnormal
Normal	TP=85.08%	FP=17.14%
Abnormal	FN=1.6%	TN=98.40%

Here, an attempt is made to classify different types of abnormal respiratory signals into wheezes, rhonchi, crackles, stridor.

Table 2.The confusion matrix for Multiclass Problem.

	Normal	Wheeze	Crackles	Stridor
Normal	99.41	0.04	0.00	0.55
Wheeze	20.35	79.61	0.04	0.00
Crackles	58.42	0.08	41.50	0.00
Stridor	34.43	0.16	0.00	65.42

From Table 2, shows a correct classification rate for normal and pathological signals. The FN=1.6% means that some pathological data were misclassified as normal case, however, the TN=98.4% demonstrates that most of the pathological data were correctly classified

V Conclusion

This paper has performed a classification of the abnormal signal from normal signal by MFCC feature and SVM classifier. The classification rate obtained proves the efficiency of the algorithm. This can be used as real time application in hospitals. The use of other feature selection methods or other cross validation techniques for the testing needs to be considered in for future studies. In the future work, to improve the performance with real data, more investigations are required on the selection of proper parameters in SVM Classifier depending upon the characteristics of the input. Also it is highly required to extend the size of the database.

REFERENCES

[1] Nikšić D., Saračević E., Ćemerlić-Kulić A., Kurspahić-Mujčić A., Bajraktarević S., Nikšić H. Evaluation of efficiency practical issues in the management of childhood asthma. Bosn J Basic Med Sci. 2005, 5(4): 40-45

[2] Mehmedagić A., Vranić E., Hadžović S., Pokrajac M., Milić J., Mehić B., Zutić H., Konjicija A. Th e new trends in theophylline therapy. Bosn J Basic Med Sci. 2002; 2(1-2) : 62-65

[3] Forkheim, Kevin E., Scuse D., Pasterkamp H. A comparison of neural network models for wheeze detection. WESCANEX 95 Communications, Power, and Computing Conference Proceedings, IEEE 1995; 1:62-65.

[4] Oud M. Lung function interpolation by means of neural-networksupported analysis of respiration sounds. Med Eng Phys 2003; 25(4): 309-316.

[5] Jain A, Vepa J, editors. Lung sound analysis for wheeze episode detection. 30th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society; 2008: 2582 - 2585.

[6] H.C. Smyllie, L.M. Blendis, P. Armitage, Observer disagreement in physical signs of the respiratory system, Lancet (1965) 412–414.

[7] R.L. Wilkins, J.R. Dexter, R.L.H. Murphy, E.A. DelBono, Lung sound nomenclature survey, Chest 98 (1990)
886–889.

[8] D.W. Cugell, Lung sounds: classication and controversies, Semin. Respir. Med. 6 (1985) 180–182.
[9] H.S. Pasterkamp, S. Kraman, G.R. Wodicka, Respiratory sounds-advances beyond the stethoscope, Am. J. Respir. Crit. Care Med. 156 (1997) 974–987.

[10] R.P. Malmberg, K. Kallio, S. Haltsonen, T. Katila, A.R.A. Sovijarvi, Classi(cation of lung sounds in patients with asthma, emphysema, (brosing alveolitis and healthy lungs by using self-organizing maps, Clin. Physiol. 16 (1996) 115–129.

[11] A. Cohen, D. Landsberg, Analysis and automatic classi(cation of breath sounds, IEEE Trans. BME 31 (1984)
585–590.

[12] J. Vanderschoot, H.J.W. Schreur, Flow and volume related AR-modeling of lung sounds, IEEE Trans. BME 13
(1991) 385–386.

[13] N. Gavriely, M. Nissan, A.H.E. Rubin, D.W. Cugell, Spectral characteristics of chest wall breath sounds in normal subjects, Thorax 50 (1995) 1292–1300.

[14] K. Anderson, S. Aitken, J.E. MacLeod, F. Moran, Lung sound transmission and reliability of the chest signs, Lancet 2 (1988) 228–229.

[15] A.R.A. Sovijarvi, J. Vandershoot, J.E. Earis (Eds.), Computerized Sound Analysis (CORSA): Recommended Standards for Terms and Techniques-ERS Task Force Report. European Respiratory Review, Vol. 10, ERS Journals
Ltd, UK, 2000, Review No. 77.

[16] Zheng H, Wang H, Wang LY, Yin G. "Lung sounds pattern analysis for anesthesia monitoring" Proceedings of the American control conference. 2005;3:1563–8.

[17] Guler, Polat H, Ergun U. Combining neural network and genetic algorithm for prediction of lung sounds. J. Med. Syst. 2005;29:217–231.

[18] Kahya YP, Yeginer M, Bilgic B. "Classifying Respiratory Sounds with Different Feature Sets" IEEE EMBS Annual International Conference. 2006:2856–9.

[19] Kahya Y, Guer E, Ozcan O, Shankur B. "Classification of respiratory sounds using crackle parameters" Engineering in Medicine and Biology Society Bridging Disciplines for
Biomedecine. 1996;3:952–3.

[20] Cohen A, Landsberg D. 1984. "Analysis and automatic classification of breath sounds" IEEE Transactions on Biomedical Engineering 319:585–90.90

[21] Dokur Z, Olmez T. "Classification of respiratory sounds by using an artificial neural network" International Journal of Pattern Recognition and Artificial Intelligence. 2003;17(4):567–80.

[22] Ryo Mukai, Hiroshi Sawada, Shoko Araki, Shoji Makino, Frequency Domain Blind Source Separation Of Many Speech Signals Using Near-Field and Far-Field Model. ,EURASIP Journal on Applied Signal Processing, Article ID 83683, 2006.

[23] Yanmei Zhan, Henry Leung, Keun-Chang Kwak, Automated Speaker Recognition for Homeservice Robots Using Genetic Algorithm And Dempster–Shafer Fusion Technique, IEEE Transactions On Instrumentation And Measurement, Vol. 58, No. 9, September 2009.

[24] Rashidul Hasan.MD,Mustafa Jamil,Golam Rabbani.MD,Saifur Rahman.MD, Speaker Identification using Mel Frequency Cepstral Coefficients. 3rd International conference on Electrical and computer engineering ICECE 2004, Dec 2004.

[25] Chih-Wei, H., and C. Lin. 2002. A comparison of methods for multiclass support vector machines. IEEE Transactions on Neural Networks, 13(2): 415-425.