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A Review on Classification of Adventitious Lung Sounds

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***Abstract*—Lungs are the vital component of human body. Now a days there are various reasons which affect the proper functioning of human lungs. Researchers have proved that, for the classification of lung sound, various processes are involved and then, to identify the normal and adventitious lung sound classifiers are needed. The whole paper is organized sequentially in which at first normal and adventitious lung sound is defined then adventitious lung sound along with its characteristic which is obtained by FFT, for classification of disease. The best feature selection is required to reduce the computational cost and to improve and enhance the accuracy. So secondly a brief observation on various features and evaluation process is done. The next step is to take classifiers for the purpose of their recognition. Finally, a comparative study pertaining to common classifiers, including various features is made in terms of attaining accuracy.**

Keywords—Adventitious lung sounds ; wheeze ; crackles ; mel frequency ceptral coefficient ; renyi entropy; kurtosis ; skewness ; lacunarity ; neural network etc.

I. INTRODUCTION

Pulmonary disease is a major cause of ill-health throughout the world. Pulmonary infections such as acute bronchitis and pneumonia are common, and interstitial lung disease is increasing in incidence. The diagnosis of these common chest diseases is facilitated by pulmonary auscultation using a stethoscope. Auscultation with a stethoscope has many limitations. It is a subjective process that depends on the individual's own hearing, experience and ability to differentiate between different sound patterns [1]. The abnormal sounds that are caused by anomalies in the lungs and bronchial tubes are termed adventitious sounds [2].

II. LUNGS SOUNDS

There are basically two types of lung sounds normal lung sound and adventitious lung sound. An adventitious lung sound further divided in two parts i.e. crackles and wheeze

A. Normal Lung Sound

Normal breath sounds have acoustically a soft character. The inspiratory phase is longer than the expiratory phase, with a ratio inspiration / expiration of about 2/1 during tidal breathing. Expiration is nearly silent [3].

B. Adventitious Lung Sound

- Wheeze: Wheeze is a continuous sound having a musical character. Acoustically, it is characterized by periodic waveforms with a dominant frequency usually over 100 Hz and with duration of ≥100 ms; hence, the sound must include at least 10 successive vibrations. Wheezes are usually associated with airways obstruction due to various causes [4].
- Crackles: Crackles are discontinuous adventitious lung sounds, explosive and transient in nature, and occur frequently in cardio respiratory diseases. Their duration is less than 20 ms, and their frequency content typically is wide [5]. The waveform of the normal lung signal, wheeze and crackles & their FFT is given below [6].

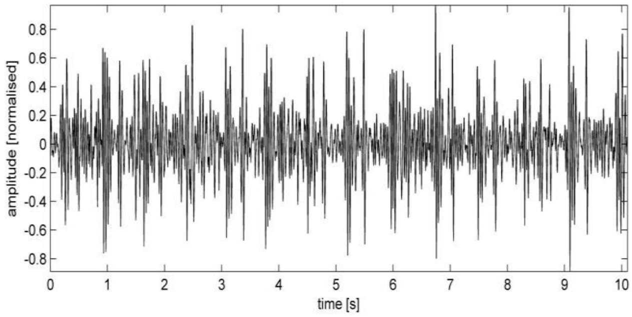

Figure 1: Normal Respiration Signal

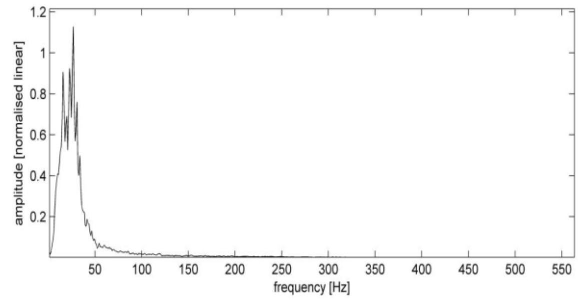

Figure 2: Fourier Transform of Normal Respiration

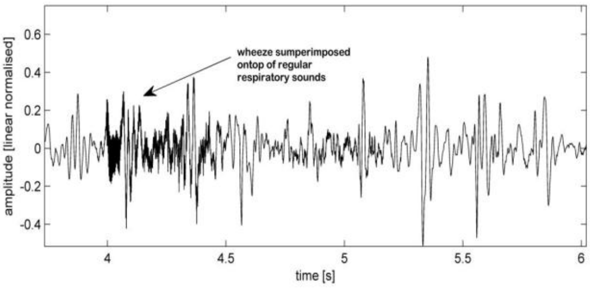

Figure 3: Wheeze Respiration Signal

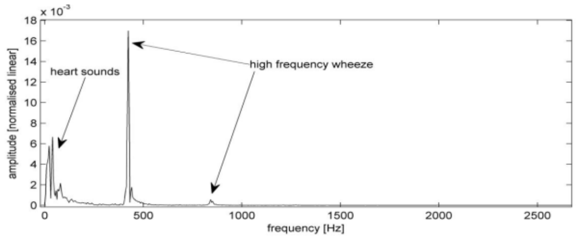

Figure 4: Fourier Plot of Wheeze Respiration

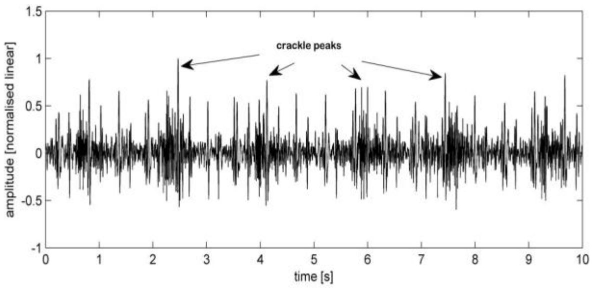

Figure 5: Crackle Respiration Signal

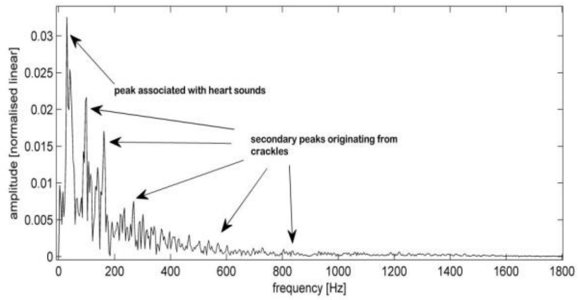

Figure 6: Fourier Transform of Crackle Respiration

III. FEATURES AND EVALUATION PROCESSES

The classification of the adventitious lung sound mainly needs two steps, first one is the feature selection and second one is the classifiers used for the classification. So here we give a brief introduction about the various features used in the classification process. Best features should be selected based on their discrimination power. ROC curve could be used to assess features. The more the area under the ROC curve, the more powerful is the feature [7]. We have number of signal processing methods like spectral analysis (e.g. FFT, wavelet), windowing, time domain expanded wave form analysis, neural networks, digital filter techniques etc [8].

A. Mel Frequency Ceptral Coefficient

The mel-frequency cepstral coefficients are calculated from the Fast Fourier Transform (FFT) coefficients, which are filtered using a triangular bandpass filter bank known as the mel scale filter bank. The linear frequency is mapped to the mel-frequency using Eq. (1),

$$\text{Mel}(f) = 2595\log_{10}\left(1+\frac{f}{700}\right) \quad \text{.........}(1)$$

where Mel(f) is the logarithmic scale of the normal frequency scale f. The logarithmic scale is then converted to time through the use of a discrete cosine transform, and the output is the set of MFCCs [9].

B. Kurtosis

The kurtosis parameter describes the shape of the probability density function in terms of the flatness or peakedness. The kurtosis value is greater for peaked distribution than that of the flat distribution. This parameter is the fourth order moment of the distribution and can be defined as-

$$\text{Kurtosis} = \frac{E[(y(n)-\mu)^4]}{(E[(y(n)-\mu)^2])^2} - 3 \quad \text{.........}(2)$$

$$= \frac{m^4}{\sigma^4} - 3 \quad \text{.........}(3)$$

where $(\cdot)$ is the expectation operator, and $\mu = E[y(n)]$ and

$$\sigma = \sqrt{E[(y(n)-\mu)^2]} \quad \text{.........}(4)$$

are the mean and standard deviation of the distribution, respectively, and (n) is the nth sample value of the lung sound signal [10].

C. Skewness

The skewness parameter measures the asymmetry of the distribution. A distribution will be asymmetric when probability density function extends unequally on the left or right sides of the center point. The skewness value is zero for symmetrical distribution and is positive or negative for asymmetrical distribution. The parameter is defined as the ratio of the third order moment and the cube of the standard deviation of the probability distribution and is calculated by-

$$\text{Skewness} = \frac{E[(y(n)-\mu)^3]}{E[(y(n)-\mu)^2]^{1.5}} \quad \text{.........}(5)$$

$$= \frac{m^3}{\sigma^3} \quad \text{.........}(6)$$

where m^3 is the third order moment of the distribution and $E(\cdot)$ is the expectation operator [10].

D. Lacunarity

The following steps are involved in calculating the lacunarity value based on gliding box algorithm.

Step 1. Compute the box mass b_{ma} for a box of length l by placing it at the origin of the dataset of length L and L is always greater than l.

Step 2. Repeat Step 1 over the entire dataset by sliding the box with one space to the right direction.

Step 3. Calculate the probability distribution (b_{ma}, l) of the box masses by dividing the box masses (b_{ma}, l) by the total number of boxes (l).

Step 4. Estimate the first (M_1) and second (M_2) moments of the probability distribution.

Step 5. Calculate the lacunarity value for the size l by dividing the second moment by the square of the first moment and can be defined as [10] –

$$\text{Lacunarity} = \frac{M_2}{{M_1}^2} \quad \text{.........}(7)$$

where $M_1 = \sum b_{ma} P(b_{ma}, l)$

$M_2 = \sum {b_{ma}}^2 P(b_{ma}, l)$

E. Renyi Entropy

The Renyi entropy is the generalized Shannon entropy which gives the degree of uncertainty in the system and is defined as-

$$H_\alpha(X) = \frac{1}{1-\alpha}\log\left(\sum_{i=1}^{n} p_i^{\alpha}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

for a given random variable X.

It can be considered as a measure of the hidden information or uncertainty for signals and uniformity for distributions. In this study, the distributions of the time-domain values of wheeze and non-wheeze signals are considered as probability mass functions and the Renyi entropies of these functions are calculated [11].

F. Mean Crossing Irregularity

The If X denotes the random variable for the interval between two successive mean crossing indices, the mean crossing irregularity is defined as -

$$= \frac{\sqrt{Var\,(X)}}{E(X)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

i.e. the ratio of standard deviation of this variable to its' mean value [11].

G. f50/ f90 Ratio

The f50 and f90 denote the frequencies where the ratio of the area under the power spectral density function to the total area is 50% and 90 %, respectively [11].

IV. CLASSIFICATION BASED ON NEURAL NETWORK

In this review we give the brief introduction about the various classifiers used for the lung signal classification based on the neural network. Artificial Neural networks are biologically inspired computer programs to simulate the way in which human brain processes information. It is a very powerful approach for building complex and non-linear relationship between a set of input and output data. Neural Network can be used for moderately correct classification of input data into categories, provided they are previously trained to do so [12].

A. Feed Forward Back Propagation Networks

In a feed forward neural network, neurons are only connected in forward direction. Each layer of the neural network is connected to the next layer, but there is no feedback. Hence, the network is trained using the back propagation training algorithm, a type of supervised training method, and the obtained results are compared with the desired results. The differentiation between the actual results and the desired results is the error. Back propagation is a technique whereby, the weights and input threshold of the neural network are changed in a way that causes this error to be condensed. Back propagation can be used with any feed forward network that uses a differentiable activation function. A feed forward back propagation neural network consists of two layers. The first layer, or hidden layer, has a tan sigmoid (tan-sig) activation function, and the second layer, or output layer, has a linear activation function. Thus, the first layer limits the output in a narrow range, from which the linear layer can produce all values. The output of each layer can be represented by-

$$Y_{N \times 1} = f\,(W_{N \times M} X_{M,1} + b_{N,1}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

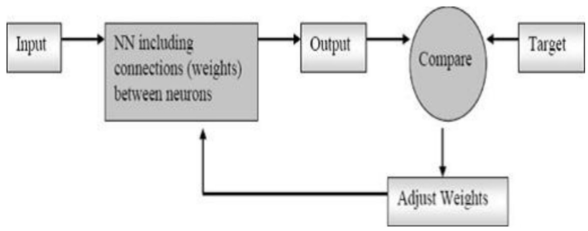

Figure 7: Block diagram for training of neural network

where, Y is a vector containing the output from each of the N neurons in a given layer, W is a matrix containing the weights for each of the M inputs for all N neurons, X is a vector containing the inputs, b is a vector containing the biases and f (•) is the activation function[12].

B. Extreme Learning Machine (ELM)

ELM is a high speed and simple learning algorithm to remove the drawbacks of conventional learning algorithms for a single layer feed forward network (SLFN). This learning technique is named as extreme learning machine (ELM) which is thousands times faster than conventional learning approaches because it avoids the adjustment of hidden layer parameters (weights and biases) during training by choosing them randomly [10] .

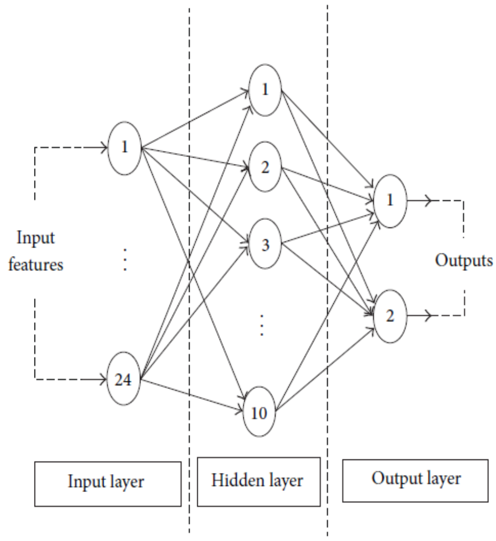

Figure 8: Structure of ELM network

C. Support Vector Machine (SVM)

Support Vector Machine is a method of machine learning, classification and recognition, which is based on statistical theorems. The classification performance of SVM is superior to traditional classification methods, especially the generalization. Error penalty parameters and the form of kernel function are two key factors of classification performance of SVM. Exchanges can be avoided if we select an appropriate inner product kernel function which makes the classification have better generalization performance and disturbance rejection capability [13].

V. CLASSIFICATION BASED ON NEURAL NETWORK AND OTHER ALGORITHM

TABLE I. COMPARISON TABLE

S. N.	Algorithm	Features used	Accuracy (%)
1	Support Vector Machines (SVM) with Radial Basis Function(RBF) Kernel	Mel frequency cepstral coefficient (MFCC)	92.19
2	K- nearest neighbor (k=1) Tenfold cross validation method	Mel frequency cepstral coefficient (MFCC)	92.26
3	Multilayer perceptron neural network using wavelet	Mean of absolute value, average power , standard devivation , ratio of absolute mean values, skewness, kurtosis	89.28
4	Feed forward back propagation neural network with LM training method	Energy index(EI) , respiration frequency , dominant frequency estimated by AR modeling, strength of the dominant frequency estimated by AR modeling	98.70
5.	Extreme learning machine	Kurtosis, sknewness ,entropy , lacunarity	92.86
6	Linear analysis (Fisher discriminant method)	Kurtosis , renyi entropy , f_{50}/f_{90} ratio , mean crossing irregularity	93.50
7.	Temporal spectral dominance	Temporal continuity and counter position , counter spread , spectral sparseness	92.7± 2.9

VI. CONCLUSION:

In this review paper we studied the different aspects used for the classification of the lung signals. The feature selection and the classifier used is the main phase of the classification process. At the first different features are selected and this features are used in the different classifier algorithm for the accurate classification of lung signal. Here we studied different features like Mel Frequency Ceptral coefficient, Kurtosis, Skewness, lacunarity, Renyi Entropy, Mean Crossing Irregularity, f50/ f90 ratio. The best feature selection save lot of computational work and it is selected by using the ROC. The most important phase is the classifier used, here we studied different type of classifier based on the neural network like support vector machine, K- nearest neighbor, Multilayer perceptron neural network, Feed forward back propagation neural network, Extreme learning machine etc. We get the best accuracy 98.70% by using the feed forward back propagation neural network with LM training method.

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