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Feature Extraction and Classification Methods for Lung Sounds

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Abstract—The lung sounds is a non-stationary signal. It is a major challenge to analyze and differentiate the type of pulmonary disorder based on lung sounds. This paper presents a detailed review of existing methods of feature extraction and classification of Lung sounds for diagnosing the various types of pulmonary disorder. The different methods like spectral analysis, Cepstrum and Mel- Cepstrum, Hilbert Huang Transform, Spectrogram and 2D representation, Wavelet method, time expanded waveform analysis, Hidden Markov model, Auto Regressive model, and Neural Network are being discussed here. All the discussed methods automatically recognise the different types of lung sounds and pulmonary disorder based on features extracted from recorded lung sounds. The paper covered all the suited existing methods which can effectively detect the lung diseases. As per the result of this analysis, it has been found that still more work is required to be done in the screening and classification of chronic Lung diseases. Chronic lung diseases, having similar symptoms and which are very hard to be distinguished and classified. So, therefore, some suitable work needed to be done so that it could effectively support the physicians for taking diagnosis decisions and for giving the correct treatment without any delay in such chronic diseases also.

Keywords: Artificial Neural Networks (ANN), Lung Sound (LS), Support Vector Machine (SVM), Wavelet Packet Transform (WPT), Wavelet Packet Decomposition (WPD)

I. INTRODUCTION

According to the epidemiological statistics of the World Health Organization (WHO) on respiratory diseases, there are 30 million asthma patients and 210 million Chronic Obstructive Pulmonary Disease (COPD) patients world-wide. Researches indicate that India accounts for 25 million asthma patients and 15 million [1-2]. Lung auscultatory method is a non-invasive and inexpensive diagnostic tool which is widely used in clinical practice to assess the state of the cardiopulmonary system [3]. Lung sounds (LS) are the sounds generated due to vibrations of lungs during air passage through it in the respiration process [4]. It actually provides information regarding functioning of the lungs and therefore plays a crucial role in detecting the lungs diseases [3]. LS are generally categorized as normal and abnormal or adventitious LS. The Tracheal, Broncho-Vesicular, Bronchial and Vesicular are the normal LS. The adventitious LS can be either continuous or discontinuous based on its duration.

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Continuous lung sounds are ronchi, wheeze and stridor, whereas Pleural Friction Rub (PFR) and crackles are discontinuous LS [5-6]. Normal LS usually obey cyclic patterns representing the air passage during the respiratory process. In cases of pulmonary diseases, it is characterized by chronic obstruction of lung airflow that interferes with normal breathing and not fully reversible [7].

Online LS recording and analysis can be used to keep track of asthma, sleep apnea and ventilation during anesthesia. It can also examine the response to broncho-constrictors, to broncho-dilators and acute bronchial challenge tests in children [8]. Auscultation through the stethoscope is just a qualitative diagnostic tool, even though it gives comparatively direct and objective information [3]. However, diagnostic outcomes using auscultation are often poor due to a lot of reasons like frequency attenuation, subjectivity errors in discriminating fine sound patterns, inter and intra observer variability, etc, [7]. The stethoscope non-linearly boosts up the sounds below 112 Hz [9] and suppresses the frequencies above 120 Hz [10], therefore, it does not give a frequency independent sounds transmission. It lacks a method of recording, has insufficient sensitivity and offers no quantitative description [10]. Disease diagnosis based on stethoscope requires physician's experience and expertise to discriminate between normal and adventitious sounds. This ability in turn, relies on the experience and hearing capability of the clinician. The impact of observer variability has been statistically proven by earlier researchers. In 1952, Fletcher [11] reported a lot of variations by the specialists to diagnose emphysema using stethoscopes. Schilling and associates [12] reported that two observers failed 24% of time to detect the presence of adventitious sounds. Elphick et al.[14] reported inability to identify respiratory signs in adults with auscultation accurately has been shown to lead to an incorrect diagnosis by physicians on 28% of occasions.

In addition to this, another important fact behind the misdiagnosis is the poor signal to noise ratio in the auscultatory analysis of LS "Thoracic lung sounds have a relatively low amplitude compared with background noise of heart and muscle sounds" [15]. Thus the LS used for the analysis purpose are often corrupted and degraded. Further researches devised Electronic auscultation, which has the advantage of signal amplification and ambient noise reduction leading to increased signal-to-noise ratio [16]. However, the factors of limitation of the human ear to discriminate closely spaced adventitious frequencies and the misinterpretation remain as a big hurdle in lung sound analysis [17].

With the advancements in lung sound recording methods and with the adoption of computer based automated methods made the lung sound based diagnosis even more better and free of subjectivity errors. Computer based lung sound analysis facilitates the analysis of change of the behavior of lung sounds, to suppress the presence of noise contaminations, to keep a record of the measurements and to analyze the lung sound features more closely with the help of graphical representations [18].

Thus, the modern computer-based analysis offers a great benefit of storage, analysis, removal of subjectivity of auscultation of LS, thereby it provides a highly accurate, objective and measurable outcome. [19-21]. Each outcome of such automated analysis can be archived for future follow-up and analysis [20]. Among the visualization methods, phonopneumogram visualizes overlapped display of LS signal and airflow in time domain during respiration [22]. The classification of LS is difficult, since their feature distributions are much overlapping [23]. Thus, the identification of effective feature extraction is essential for reliable classification [24]. This paper is a review of methods for feature extraction from LS and the classification.

II. REVIEW OF METHODS FOR FEATURE EXTRACTION FROM LUNG SOUND AND THE CLASSIFICATION

A. Methods based on spectral analysis

Literature [25] classified LS captured from emphysema, asthma, fibrosis alveolitis and healthy subjects by using Self Organizing Maps (SOM) based on FFT spectra. To examine the effect of bronchodilator in patients affected with asthma,the spectral analysis of LS was carried out in[26]. The major variability of Fourier power spectra was determinedusing Multi-scale Principal Component Analysis (PCA) in [27]. In [28], Fourier spectra were used forclassification with a 1-nearest neighbor technique. Power raising transformation was adopted to carry out the optimization of Fourier spectra

In [29], the spectral characteristics of the chest wall and tracheal LS were analyzed. The spectral pattern with exponential delay of LS intensity with respect to increasing frequency was observed. The spectral pattern of normal chest wall LS was found to have an exponential decay of sound amplitude with increasing frequency. Log-log presentation of the sound spectra represented a negative linear slope in case of both inspiratory and expiratory cycles of LS captured at all of the chest wall pick-up locations.

Literature [30] characterized crackles captured from patients affected with heart failure, pneumonia and fibrosis at a constant breath rate. The maximum frequency was observed with the application of discrete pseudo Wigner-Ville distribution and an objective method to estimate the maximum frequency which is a modified geometric method. In addition to this, spectra of crackles were also examined based on the variations of tidal volume and breath rate. The effect of the high-pass filter cut-off frequency on the behavior of crackles were also evaluated in this study. Higher high-pass filter cut-off frequency permits greater amplification which further changes the Two Cycles Duration (2CD) index and maximum frequency. It is reported that the crackles recorded as per the guidelines of Computerized Respiratory Sound Analysis (CORSA) have shorter 2CD indexes and higher frequencies in comparison to those reported previously. The results showed that crackles originated from fibrosis could be discriminated from the ones originated by the pneumonia and the heart failure, using 2CD indexes and the maximum frequency. The results pointed out that the maximum frequency and the 2CD indexes may allow crackles generated by fibrosis to be distinguished from the ones generated by the heart failure and pneumonia. However, differentiation between heart failure and pneumonia crackles using these two indexes were not possible. Fenton at al. [31] analyzed the power spectra of the sounds for peaks of high amplitude and high frequency as indications of wheezing.

The LS were characterized by their mean power spectral density, summed into feature vectors across the 0 to 800 Hz frequency spectrum in Waitman et al. [32]. Each breath sound signal was splitted into two segments, i.e., inspiratory segment and expiratory segment. Sounds were classified as normal or abnormal and the performance of different configurations of Back-Propagation Neural Network (BPNN) configurations were analyzed.

The power spectra of vesicular breathing, rale and wheeze from 40 subjects were analyzed by Band Selectable Fourier Analysis (BSFA) in Xu et al. [33].

In Z. Dokur [34], a rectangular window was created that covers one LS cycle. The normalized LS signal was splitted into 64 segments. The power spectrum of each segment was calculated and synchronized summation of it was determined. Feature vectors were created with the help of averaged power spectral components. In the study, classification outcomes of Grow and Learn (GAL) network, Multi-Layer Perceptron (MLP), and a Incremental Supervised Neural Network (ISNN) were analyzed to discriminate various LS categories i.e., broncho-vesicular, bronchial, vesicular sounds, wheezes, crackles, stridor, squawk, grunting and friction rub. Masada et al. [35] determined a series of power spectra by FFT for all LS and calculated a few quantity of component spectra by Independent Component Analysis (ICA) for all overlying sets of tens of successive power spectra. The component spectra acquired from different LS were put into a single set and clustering was performed repetitively. Those spectra were assumed to have robust similarity whose component spectra repeatedly belongs to the same cluster. Qiu et al.[36] demonstrated automated wheeze detection using auditory modeling, termed as the Frequency and Duration Dependent Threshold (FDDT) algorithm. The thresholds were determined with the help of auditory modeling, rather than using a constant threshold. The threshold is computed from the energy of only a selected bandwidth. Instantaneous frequency (IF) computed by Empirical Mode Decomposition (EMD) was used to analyze LS in the literature [37]. In the article [38], the EMD was employed to detect fine and coarse crackles.

The IF analysis presented in [39] produced a high definition depiction in the Time-Frequency (T-F) plane of LS signals. The neglected phase details in spectrogram had been used for the determination of IF and the successive temporal-spectral dominance. Features set had been calculated to determine the shapes of the procured individual TF contour and hence, upgraded the recognition of multi-component signals. In the literature [40] a set of features based on the temporal characteristics of the filtered narrowband signal to classify LS into normal and continuous adventitious was proposed.

LS were first decomposed in the T-F domain and then features were extracted from a selected frequency bins, which possess definite signal characteristics based on Auto-Regressive (AR) averaging, sample entropy histograms distortion and the recursively measured instantaneous kurtosis. The study reported the mean classification accuracies of 97.7% for inspiratory and 98.8% for expiratory segments, respectively, using Support Vector Machine (SVM) classifier.

B. Hilbert-Huang Transform (HHT)

The Hilbert–Huang transform (HHT) is a method used to decompose any signal into intrinsic mode functions (IMFs) and to get instantaneous frequency information. It works competently over non-stationary as well as nonlinear data.HHT algorithm is actually like an empirical approach which can be applied to a data set, rather than a theoretical tool.

In [41], feature extraction of crackles was performed using Fractional Hilbert Transform. HHT was used in Z. Li and M. Du [42] to detect and classify crackles. By detecting peaks in the T-F distribution derived from HHT, segments were extracted and were identified as crackles.

The literature [43] analyzed the performance of the Hilbert-Huang Spectrum (HHS) on fine and coarse crackles, simulated and real ones. Literature [44] used HHT for the recognition of Velcro rales. HHT was adopted to extract the energy weight in several frequency bands of crackles and to find out the section of crackles during late inspiration. Velcro rales differentiation from the crackles was performed using SVM based on the HHT-derived measures.

In S. Icer and S. Gengec [45], the feature extraction process for discriminating ronchi and crackles from normal sounds consists of three signal-processing components, f_{min}/f_{max}, the frequency ratio obtained from the Power Spectral Density (PSD) computed using Welch method. The exchange time of the IF and the average IF was calculated by the HHT. The Eigen values were determined from the Singular Spectrum Analysis (SSA). SVM classifier was used to discriminate the rhonchus, crackles and normal LS.

C. Cepstrum and Mel-Cepstrum

J. Xu, J. Cheng and Y. Wu [46] introduced a cepstral method to analyze the acoustic transformation behavior of the respiratory system. The LS signal was initially split into segments, which were further represented by a decreased number of cepstral coefficients as discussed in [47]. Those segments were distinguished as wheezes or normal LS, by applying the Vector Quantization (VQ).

Parametric analysis based on cepstral analysis was employed by Tavares et al. [48] to discriminate pathological voices of speakers affected by vocal fold edema. Delta cepstral, cepstral, weighted cepstral and weighted delta cepstral parameters were used as features to diagnose the abnormalities of the pathological voices in contrast to the normal voice. A VQ was used which was linked with quantification of distortion to classify the speech signal. VQ was used to classify the speech signal using VQ in association with distortion measurement.

M. Bahoura and C. Pelletier [49] proposed the cepstral analysis and Gaussian Mixture Models (GMM) to classify wheeze and normal LS. The LS signal was split in overlapped segments, such segments were distinguished using Mel-Frequency Cepstral Coefficients (MFCC) or Sub-Band Based Cepstral parameters (SBC).

Literature [50] classified normal LS and wheezes using Cepstral analysis in GMM. The sound signal was divided into overlapping segments. Each segment was characterized by MFCCs. Literature [51] discussed preliminary detection of respiratory disorders like Bronchitis in the children living in the rural areas with MFCC. AR, Wavelet Transform (WT) and MFCC was used in [52] for feature extraction to discriminate between wheeze and non-wheeze. M. Bahoura [53] classified LS into normal and wheeze classes. The feature extraction techniques include linear predictive coding, WT, Fourier transform and MFCC conjointly with the classification methods based on VQ, Artificial Neural Networks (ANN) and GMM and, using Receiver Operating Curves (ROC) were evaluated. Literature emphasized on the application of an optimized threshold to classify the normal and wheezes LS. In addition to this, a post-processing filter was used to enhance the classification performance. S. Aydore [54] described the detection of presence of wheeze and non-wheeze epochs in LS captured from asthma and COPD subjects. Features which were extracted from LS include ratio irregularity, mean-crossing irregularity and Renyi entropy. Two approaches were used regarding the calculation of these features. The first approach includes the split of the entire data in three feature dimension feature spaces, which were considered to be Gaussian distributed. Thereafter, a decision rule was used for two dissimilar Gaussian random vectors. Fisher Discriminant Analysis (FDA) was adopted to estimate the three dimensional data from the single dimensional space that discriminates the two classes. Later, for the two dissimilar Gaussian variables, a decision rule was applied. Literature [55] also was based on the Gaussian Mixed Models (GMM).

D. Spectrogram and 2-D representations

N. Sahgal [56] developed a LabVIEW based application to classify lung sounds through power spectrum and spectrogram. Riella et al. [57] introduced 'spectrogram image processing' of LS cycles as a framework for automated wheezing identification. The spectrogram was produced from the acquired LS signal. The obtained spectrogram image was allowed to pass through a bi-dimensional convolution filter and a limiter to adjust the contrast and to separate out the higher frequency constituents.

The spectral average was determined from the obtained spectrogram and is fed as inputs to a Multi-Layer Perceptron (MLP) artificial neural network. In literature [58] LS of each respiratory cycle had been normalized and its spectrogram was computed. The spectrogram image processing was carried out using a 2-D convolution filter and a half-threshold to boost up the contrast and to separate its highest amplitude constituents. Further, the spectral projection was determined and archived as an array.

The greater values of spectral projection and its relevant spectral values were positioned and applied as inputs to a MLP ANN which provides automated detection of wheezes. The study resulted in accuracy of 84.82% in the detection of wheezing for an isolated breath cycle and an accuracy 92.86% for the identification of wheezes out of groups of breath cycles of the same subject.

In [59], sample entropy (SampEn) histograms were applied to detect the presence of wheeze out of filtered narrow band LS signals.The LS signals were split initially into inspiratory as well as expiratory segments. T-F of each section was procured with the help of Gabor spectrogram. Later on, the histograms of the chosen frequency bins of the SampEn plane were computed. The study has adopted the mean distortion of the histogram for wheeze detection.

Mor et al. [60] introduced an automated multi-sensor breath sound mapping device to analyze, record, and present the breath sound distribution in a dynamic grayscale map. In [61] Vibration Response Imaging (VRI) was used to map LS from 40 sensors to a 2-D grayscale image.

E. Wavelet approaches

Abbasi et al. [62] integrated wavelet based feature extraction and classification using SVM. The classification of adventitious LS was carried out using Discrete Wavelet Transform (DWT) and a classifier based on a Radial Basis Function (RBF) neural network as discussed in [63].

In literature [64], WT was applied to a window of 256 samples. Feature vectors were determined from the wavelet coefficients. Dynamic programming was used to select the statistically significant feature sets. Classification was carried out using Grow and Learn (GAL) neural network. Literature [65] described wavelet analysis to identify the frequency-power distribution of the unstable LS to recognize the healthy subject. In [66], WT was used to decompose the LS signals into frequency sub-bands and statistical features were computed extracted from those sub-bands to show the wavelet coefficient distribution. LS was categorized as wheeze, squawk, stridor, crackle, rhonchus or normal using an ANN based system which is trained by applying the Resilient Back Propagation Algorithm (RBP). The Continuous Wavelet Transform (CWT) was applied for Wheeze Analysis in [67]. Literature [68] have demonstrated the extraction and analysis of the nonlinear behavior of asthmatic wheezes. To achieve this, CWT was united with third-order statistics/spectra. The study [69] statistically analyzed the nonlinear behavior of wheezes and their transformations with time. CWT was applied united with third-order spectra to characterize the analysis domain. The non-linear interactions of wheezes harmonics and their alterations with time were recognized using bi-coherence and instantaneous wavelet bi-spectrum, combined with bi-phase and bi-amplitude curves. Total 23 feature set was computed for analyzing the nonlinear behavior of wheezes. Generalized and detailed aspects were used to form a feature set so as to obtain the trends and local behavior, which was observed in the nonlinear behavior of the wheezes harmonics over time. The proposed set of features were analyzed on wheeze LS, captured from asthma and COPD patients. Literature [70] demonstrated the use of adaptive wavelets to detect the pathological changes of the lungs which generate sounds with computable irregularities. A wavelet packet based method was adopted to diagnose abnormal LS in Pesu et al. [71]. The lung sound signal was split into sections. Feature vector was formed for classification using the results to recognize the finest wavelet packet decomposition. Each section was classified as normal LS, wheezes or crackles using Learning VQ. The literature [72] classified features of wheezes as spectral and temporal characteristics and used it to examine the captured LS including wheezes from asthmatic patients. Wavelet Packet Decomposition (WPD) and T-F techniques were used. For crackle detection, feature sets having scale and frequency information were calculated in [73], with the help of time-scale (TS) and T-F analysis. Various types of windows and wavelets like Blackman, Gaussian, Hanning, Bartlett, Hamming, Rectangular and Triangular used for TF analysis, and Mexican Hat, Paul, and Morlet were adopted for TS analysis. Such analyses were examined for 6000 signals. In order to get the best crackle detection outcome. To obtain the improved crackle detection outcome, the frequency components having no-information (above 2400 Hz and below 150 Hz) were eliminated using Dual-Tree Complex Wavelet Transform (DTCWT). The ensemble and the individual features were given as input to MLP, *k*-Nearest Neighbor (*k*-NN) and SVM classifiers. Classification results were compared and examined using these features over non-pre-processed and pre-processed data. An integrated system for crackles recognition was presented in X. Lu and M. Bahoura [74]. This system includes the three serial modules i.e., crackles segregation from LS using a Wavelet Packet Filter (WPST–NST), detection of crackle using Fractal Dimension (FD) and GMM for crackle classification. To detect crackles from the LS, two thresholds were decided both in frequency and time domains. The output of crackle peak detector and WPST-NST were subjected to pass through a denoising filter to localize each crackle using their FD. The Gaussian Band-Width (GBW), Peak Frequency (PF) and Maximal Deflection Width (MDW) were the features computed from LS. Coarse and fine crackles were recognized using GMM.

Wavelet Networks (WN) had been utilized to quantify and parameterize crackles with an intention to represent the waveform with a lesser set of parameters by M. Yeginer and Y.P. Kahya [75]. At the node of double and single node networks, the complex Morlet wavelets were applied to model the waveforms with the double-node rendering smaller modeling error. In Y. P. Kahya and M. Yeginer [76], WN was used to characterize and classify the fine and coarse crackles.

First node of the wavelet function was trained to fit the crackles and whereas, the second wavelet node was used to represent the presence of error in the first node. Scaling, frequency, time-shifting, and two weight factors were the WN node parameters of cosine and sine components were used as features for crackles classification. The objective of M. Yeginer and Y. P. Kahya [77] was to demonstrate the existence of another new type of crackle namely, medium crackle, besides the available types of crackles i.e., coarse and fine crackles. Furthermore, the study explored the various parameter values for each type of crackle. The Expectation– Maximization (EM) algorithm was applied for clustering and the obtained cluster numbers were tested with Bayesian Inference Criterion (BIC). Four parameter sets were computed from the processed crackle LS samples using zero crossings of crackle waveform, spectral components of crackles, single node WN modeling and double-node WN modeling.

F. Time expanded waveform analysis

Literature [78], [79], [80] and [81] characterized LS visually by Time Expanded Waveform Analysis (TEWA). Literature [80] investigated characteristics of lung crackle characteristics through TEWA in patients with asbestosis (AS), Asbestos-Related Pleural Disease (ARPD) and Left Ventricular Failure (LVF). Bettencourt et al. [81] applied lung sound mapping and TEWA to four common diseases, Interstitial Pulmonary Fibrosis (IPF), COPD, Congestive Heart Failure (CHF) and pneumonia. Twenty subjects were studied in each group. They also studied 15 subjects without evidence of lung disease. Differences in timing, character, and location were observed, which allowed separation between these groups. Multiple logistic regression models were created and tested by the bootstrap method. Total 79% of subjects were correctly classified using regression models. Area under the ROC ranged from 0.96 for IPF and CHF to 0.80 for COPD.

G. Maximum likelihood approaches based on Hidden Markov models

S. Matsunaga et al. [82], M. Yamashita [83] and Himeshimaat al. [84] classified normal and abnormal LS based on a Maximum Likelihood (ML) method making use of Hidden Markov Models (HMM). In [84], the spectral as well as power features were extracted from LS signal and a stochastic procedure was adopted to detect abnormal LS.

Literature [85] made use of LS samples from multiple auscultation points. Following the estimation of the acoustic likelihood for every phase of respiratory cycle on the basis of the ML approach using HMM alongwith a segmental bigram, the diagnosis was performed on the basis of the correlation of the average likelihood of all auscultation points between a healthy subject and a patient.

H. Auto-regressive model based approaches

Literature [86] deals with the evaluation of various parameterization methods for LS captured from the posterior thoracic location for the healthy versus adventitious LD classification. For creating feature vectors, the eigenvalues of covariance matrix, Multivariate Autoregressive Models (MAR) and Univariate Auto Regressive (UAR) were used. These feature vectors were given as input to a Supervised Neural Network (SNN). Feature parameters were obtained from AR models applied to overlapping segments of LS in literature [87]. LS of diseased and normal subjects were assessed using AR in [88].Two reference libraries were built using the Using the AR vectors.Two classifiers, a quadratic and k-NN classifier, were correlated and their performances were validated for various model orders. The classification outcome was found to be better for model order 6. In [89], the modeling of 14-channel LS was done considering a 250-point second order Vector Autoregressive (VAR) method. The obtained model features were fed as input to a SVM classifier having a Radial Basis (RB) kernel, to differentiate the healthy, interstitial pulmonary disease and bronchiectasis subjects. In literature [90], k-NN classification outcomes were compared using different sets of features derived from LS signals captured from four different posterior chest areas. Features like percentile frequency parameters, principle components and 6th order AR model coefficients were calculated. K-NN classifier performance was evaluated using different features sets for four different posterior chest locations. The literature [91] presented a real time diagnostic system to discriminate healthy and pathological LS using Motorola's 56311 Digital Signal Processor (DSP). This diagnostic system had two inputs, one input was connected to a microphone, while other input was connected to a flow meter to identify the inspiratory as well as expiratory cycle during the respiratory process. The sampled LS was split into six phases using the signal received from the flow meter. Each phase was further split into 10 conjoining segments. AR model of order 6 by means of the Levinson-Durbin algorithm was used for modeling of each segment. The classification was done using two classifiers: k-NN with Itakura and Euclidean distance measures, and minimum distance classifier with the Mahalanobis distance measure. In [92], the LS data were split into segments, namely, early, mid, late inspiration and expiration. Neural classifiers were used to classify each segment. The ratio of expiration to inspiration durations, prediction error and AR parameters obtained from segmented sound signals were used to form the feature set. Various experiments were carried out to distinguish the healthy and adventitious LS. The obtained results showed the dependence of sub-segment for different diseases. L. Shengjun and L. Yi [93] proposed AR model bi-spectrum estimation algorithm for feature computation. Bi-spectral cross correlation analysis was used for selecting the AR model orders, which were used to determine parametric bi-spectrum of the LS signals. Bi-spectrum features were extracted from LS signals captured from healthy, pneumonia and asthmatic subjects, and were compared in a bi-frequency domain. Slice spectrum parameters and peaks of bi-spectrum normalized bi-spectral entropy were chosen as the feature sets for classification. Hernandez et al.[94] integrated multichannel recording of LS using an array of microphone, computation of feature vector with the help of Multivariate AR (MAR) model, dimensionality reduction of those feature vectors using PCA and PCA, followed by the classification using SNN classifier. Mendezat al.

[95] explored the ability of the Time-Variant Autoregressive (TVAR) model to diagnose the coarse and fine crackles in LS. The TVAR was used to process the real LS having crackles and the normal LS inserted with simulated crackles. The coefficients of the TVAR were obtained through an adaptive filtering prediction scheme.

In Kahya et al. [96] from the LS acquired from a microphone placed on the posterior chest area. Single breath cycle was split into sixty segments, out of which three different feature sets including consisting of wavelet coefficients, crackle parameters and 6th order AR model coefficients were calculated. Various classification experiments were conducted on each respiratory phase, to classify pathological and normal LS using ANN and k-NN classifiers. LS of healthy and diseased subjects were examined through the AR model parameters and frequency spectrum to form a LS based diagnostic aid as discussed in C. A. Yilmaz and Y. P. Kahya [97]. Two reference libraries were formed for each respiratory phase and for each channel separately for multi-channel LS data acquired from healthy and diseased subjects. A k-NN classifier was used for a multi-channel classification.

I. Miscellaneous methods

Emmanouilidou et al. [98] proposed a model based on a biomimetic multi-resolution analysis of the spectro-temporal modulation details in LS of pediatric auscultations. Baydar et al.[99] applied signal coherence method for parametric representation and automatic classification of the LS. In literature [100], the Recurrence Quantification Analysis (RQA) technique is used. In [101], characterization of LS was done using Voice Activity Detection (VAD) algorithm, which was applied to determine the acoustic respiratory signal energy during breath hold and breathing condition. The normal and the abnormal subjects were distinguished in [102] by using the morphological complexities of the LS.The lacunarity, skewness, kurtosis and sample entropy were estimated to determine the morphological embedded complexities. Such features were calculated from 20 abnormal and 10 normal subjects using SVM and Extreme Learning Machine (ELM). This algorithm resulted in the classification accuracy of 92.86%, sensitivity of 86.90% and specificity of 86.30% using these feature vectors. In [103], a technique for the detection of non-stationary bio-acoustic signals, i.e., bowel sounds and explosive LS, was presented. In this study, kurtosis (zero-lag fourth-order statistics) was used to create an Iterative Kurtosis-based Detector (IKD). The important peaks of kurtosis were identified using IKD. Those peaks were detected within a sliding window along the LS signal, which represent the existence of non-Gaussianity in the raw LS signal. The automated discrimination of discontinuous lung sounds i.e., Squawks (SQ), Coarse Crackles (CC) and Fine Crackles (FC) was introduced in L. J. Hadjileontiadis [104]. The study proposed classification based on a texture based approach using the lacunarity of lung sounds that discriminated the distribution of SQ, CC and FC across the respiratory cycle. Literature [105] investigated the efficacy of state space parameters of the LS acquired from the asthmatic and healthy subjects under various respiratory conditions. The objective was to interpret the diagnosing ability of parameters like Lyapunov exponents, embedding dimension and time delay. LS were acquired from the right lower lobe position of the asthmatic children and few healthy subjects during pre and post-bronchial provocation via post-bronchial dilation (BD) and methacholine challenge (MCh). Inspiratory air flows assumed during capturing of LS were 7.5, 15, or 22.5 mL/s per kg (±20%). The average values of time delay was found to be decreased with the increasing flows of sounds recorded from healthy subjects. The value of percentage of Lyapunov exponent decreased and the time delay was found to be increased for the subjects who showed broncho-constriction, during post-MCh, and returned to pre-MCh values post-BD. The literature suggested that time delay and the presence of positive Lyapunov exponents could be used to develop a model to predict variations in the respiratory status.

Hadjileontiadis et al. [106] performed a FD analysis of the Bowel Sounds (BS) and LS acquired from healthy and patients with bowel and pulmonary pathology, respectively. The study identified the time location as well as the duration of LS and BS, in spite of the fluctuations either in time duration and/or amplitude. After broncho-constriction, LS of children usually differ from baseline LS in terms of amplitude and pattern behavior. To test these hypotheses, fractal based and time-domain analyses have been used to LS signals captured from eight children under the age group of 9-15 years by pre- and post-methacholine challenge (MCh) as discussed in [107]. Sakaiat et al.[108] presented a sparse representation-based method to identify adventitious LS. As the noise cannot be shown sparsely by any bases, clear LS and abnormal LS from noisy LS through the sparse representation can be determined. The level of abnormality could be determined using these clear sound components. The pulsating waveforms were identified as crackles, which were detected in the adventitious LS. The most important features in frequency and time domain were identified using Statistical Overlap Factor (SOF) to diagnose the presence of tuberculosis presented by Beckerat al.[109]. Those features were applied to train an ANN to discriminate the auscultation recordings into their normal or TB-origin categories. Habukawa et al. [110] recorded LS from the trachea and the right anterior chest location using two sensors, and determined the acoustic transfer behavior in between the two points, which showed the correlation between the attenuation and frequencies during LS propagation. The tracheal sound index (TRI) and chest wall sound index (CWI) were the features extracted from those transfer characteristics. Breath sound intensity (BSI) was the another parameter, which was proposed to examine whether BSI can detect asthma better than TRI or CWI. It was observed that, there was a valid difference in values of TRI and BSI in between asthmatic and non-asthmatic children ($p = 0.007$, $p < 0.001$), and a valid difference in CWI and TRI values in between the well-controlled and not-well controlled groups ($p < 0.001$). BSI differentiated between the two groups with the specificity of 84.2% and sensitivity of 83.6%.

Authors exhibited the confidence asthma control could be evaluated using BIS. L. J. Hadjileontiadis [111] evaluated the outcomes of an automatic Discrimination Analysis (DA) method to differentiate coarse crackles (CCs), fine crackles (FCs) and squawks (SQs). The proposed method observed the dissimilarity in the oscillatory pattern of SQs, CCs and FCs. The capacities of ANN and human examiners to classify LS were compared in [112] on asthmatic LS. Folland et al.[113] assessed the outcomes Constructive Probabilistic Neural Network (CPNN) in comparison to Radial Basis Function Network (RBFN) and MLP classifiers to classify wide range of tracheal-bronchial LS. A comparative chest diseases diagnosis was realized by using multilayer, probabilistic, learning vector quantization and Generalized Regression Neural Networks (GRNN) in [114]. F. Ayari, M. Ksouri and A. Alouani [115] employed statistical and fuzzy nonlinear classifiers to categorize crackles. A hierarchical decision fusion scheme was discussed in Guler et al. [116]. LS from three different classes were split into segments which were combined to create six different phases of breathing cycle. MLP classifiers were used to differentiate the parameterized segments from every phase. The decision vectors obtained from different phases were joined together using nonlinear decision combination function to get a final opinion on each subject. In [117], Fisher Discriminant method (FD) was used to discriminate the wheeze and non-wheeze windows in LS captured from COPD and asthma patients by using Fisher Discriminant method (FD). Daniel Sanchez Morillo et al. [118] presented a different method analyzing the breathing sound of pneumonia patients. The feature extraction was done using short time Fourier transform and for dimensionality reduction, method of Principal component analysis was used, and classified using Probabilistic Neural Network (PNN), and was found to be 77.6% accurate. Rami J. Oweis et al. [119] suggested a respiratory sound feature extraction using autocorrelation,which was done to apply the Fast Fourier Transform and classification for diagnosis was done using Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) with 98.6% accurate.

Nahit Emanet et al.[120] reported a machine learning method to detect asthma. The feature extraction was carried out using wavelet decomposition method. The ANN and adaboost along with the Random Forest method were used to classify asthma and the classification accuracy was observed to be 90%. In [121], an adaptive neuro fuzzy inference based system presented by N. Kins Burk Sunil which successfully classified various classes of LSs as wheeze, crackles, stridor and normal, providing a quantitative basis for abnormal respiratory sound recognition. B. Flietstra et al. [122] proposed automated method for analysis of crackles in patients with Interstitial Pulmonary Fibrosis (IPF). This method was presented as to distinguish the crackle in case of patients with IPF with that of patients with Congestive heart failure (CHF) and Pneumonia (PN). The software automatically detected and counted crackles. For disease classification neural networks and support vector machines were used. IPF crackles were detected with an accuracy of 86% and that of CHF with 82%.

III. DISCUSSION

This paper gives a comprehensive review of the existing methods used to determine the lung sound features and the methods applied for classification of lung sounds to diagnose the exact type of pulmonary disorder. The different authors have used different methods for feature extraction such as, Spectrogram and 2D wavelet transform, principle component analysis, sample entropy (Sampen) histograms, adaptive crisp active contour models (ACACM), Hilbert Huang transform (HHT), cepstral coefficient, Variant Autoregressive (TVAR) model, Time Expanded Waveform Analysis (TEWA), Vector Autoregressive (VAR) process, Wavelet Packet Decomposition (WPD), Fractional Hilbert Transform, Dual-Tree Complex Wavelet Transform(DTWT), Complex Morlet wavelets, Univariate Auto Regressive (UAR) and the Multivariate Autoregressive Models (MAR), AR model bi-spectrum estimation, FD-based detector and automatic Discrimination Analysis (DA) method. For feature extraction to be done more effectively, wavelet based time frequency analysis method can be used, as this method could be applied for non-stationary signals easily. After feature extraction and segmentation, for the detailed analysis of identification of diseases different classification methods like- MFCC, SVM, MLP, extreme learning machine neural network (ELMNN), GMM, Maximum Likelihood (ML) approach using Hidden Markov Models (HMM), k-NN classifiers, GAL, ANN, Constructive Probabilistic Neural Network (CPNN) Supervised Neural Network (SNN), Deep Convolutional Neural Networks, Constructive Probabilistic Neural Network (CPNN), Gaussian Mixture Models (GMM) and Random Forest with adaboost have been used. In this paper all the classification methods have been discussed, and identified that Support Vector machine (SVM) performed with the highest accuracy of 97.7% and 98.8% for inspiratory and expiratory segments and, so preferred as the best classifier by the authors.

Enormous work is available for extraction of features and classification of lung sounds for diagnosing the type of lung disorder. Many studies have proved successful in diagnosing lung disorder based on lung sound. However, there are some chronic diseases which exhibit similarity in their symptoms, because of which they are often misdiagnosed. More work is still required to diagnose and discriminate against such chronic diseases. It will help physicians to make effective diagnostic decisions in such chronic diseases too.

IV. CONCLUSION

The chronic pulmonary diseases are nowadays a big problem in the whole world, leading to increased death rates. It is required to produce an accurate method to ease the diagnosis and cure. With this study, It is understood that, for feature extraction, wavelet based methods and mel-frequency cepstral coefficients are suitable for any kind of lung sound signal. It is also observed that a support vector machine is the best disease classification method which can help for taking diagnostic decisions.

The existing methods have tried to cover the detection and differentiation of the different lung sounds, but still some more work is required to be done to identify and discriminate the lung diseases, specifically, the chronic lung diseases, which show similar symptoms.

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