

Multichannel lung sound analysis for asthma detection

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ABSTRACT

Background and objective: Lung sound signals convey valuable information of the lung status. Auscultation is an effective technique to appreciate the condition of the respiratory system using lung sound signals. The prior works on asthma detection from lung sound signals rely on the presence of wheeze. In this paper, we have classified normal and asthmatic subjects using advanced signal processing of posterior lung sound signals, even in the absence of wheeze.

Methods: We collected lung sounds of 60 subjects (30 normal and 30 asthma) using a novel 4-channel data acquisition system from four different positions over the posterior chest, as suggested by the pulmonologist. A spectral subband based feature extraction scheme is proposed that works with artificial neural network (ANN) and support vector machine (SVM) classifiers for the multichannel signal. The power spectral density (PSD) is estimated from extracted lung sound cycle using Welch's method, which then decomposed into uniform subbands. A set of statistical features is computed from each subband and applied to ANN and SVM classifiers to classify normal and asthmatic subjects.

Results: In the first part of this study, the performances of each individual channel and four channels together are evaluated where the combined channel performance is found superior to that of individual channels. Next, the performances of all possible combinations of the channels are investigated and the best classification accuracies of 89.2(±3.87)% and 93.3(±3.10)% are achieved for 2-channel and 3-channel combinations in ANN and SVM classifiers, respectively.

Conclusions: The proposed multichannel asthma detection method where the presence of wheeze in lung sound is not a necessary requirement, outperforms commonly used lung sound classification methods in this field and provides significant relative improvement. The channel combination study gives insight into the contribution of respective lung sound collection areas and their combinations in asthma detection.

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1. Introduction

The loss of health due to Asthma is a major concern as it has a very high burden of disability. More than 334 million people suffer from asthma worldwide [1]. Asthma causes symptoms such as wheezing which is regarded as the most common symptom [1,2], shortness of breath, chest tightness and cough that vary over time in their occurrence, frequency and intensity [3]. These are associated with variable expiratory airflow, i.e., difficulty in breathing air out of the lungs due to bronchoconstriction (airway narrowing), airway wall thickening, and increased mucus. However, they may be triggered or worsened by factors such as viral infections, allergens, tobacco smoking, exercise and stress [3]. The ignorance in diagnosing or treating asthma has detrimental effects on the pa-

tients' quality of life due to worsening of lung function [4]. It may finally result in remodeling of the airways and increase in asthma morbidity [5–7]. Therefore, there is an urgency to develop a suitable asthma detection system for its diagnosis.

Asthma is suspected clinically with a medical history and clinical examination, but the diagnosis is confirmed by spirometry. It is used to assess the airflow limitation and the reversibility of the same on use of an inhaled bronchodilator. Spirometry test provides an objective, quantifiable measure of the lung function [8]. However, this method does not provide a specific etiological diagnosis, fails to detect an obstructive-restrictive defect and is not considered user-friendly for its requirement to have supervision of skilled operators [8]. Therefore, computerized lung sound analysis for asthma detection has come into focus which is non-invasive, cost-effective and patient-friendly. The computer based study offers immense advantages with respect to the storage, analysis, and communication of the lung sounds for diagnostic purpose.

An automated lung sound analysis mainly consists of three steps: preprocessing, feature extraction and classification. There

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have been efforts to use different types of features and classifiers for asthma and wheeze detection [9,10] from lung sound signals. In frequency domain analysis of lung sounds, Fourier spectrum and *power spectral density* (PSD) based features were used for wheeze [2,11–13] and asthma [14] detection task. PSD based features were also used to measure airway obstruction of asthma patients by comparing the result with the spirometry [15], and to assess the bronchodilator effect in healthy and asthmatic subjects [16]. In time-frequency domain analysis, wavelet transform [17], short-time Fourier transform (STFT) [18,19] based features were used for wheeze detection. Some researchers used audio perception based cepstral features, e.g., mel-frequency cepstral coefficients (MFCCs), inverted mel-frequency cepstral coefficients (IMFCCs) and linear prediction cepstral coefficients (LPCCs), for lung sounds classification that included wheezing sound [20–22]. Moreover, the effectiveness of the classifiers like *artificial neural networks* (ANN), *support vector machine* (SVM), Gaussian mixture models (GMM) and k-nearest neighbors (k-NN) [23] have also been investigated for lung sounds classification [10].

While there are quite a few efforts to develop wheeze detection algorithms, its usefulness in asthma detection is limited as wheezes can be heard in several diseases other than asthma [24,25], and wheeze is not always present during active asthma [26]. For lung status examination, we find a large body of work by the researchers using single sensor based system [2,11,13–16,18,21]. However, acquisition of lung sounds from multiple positions simultaneously can be advantageous for more accurate diagnosis of asthma because it can capture information from all over the lungs at a particular time. The multi-sensor based system described in [12] used eight microphones on patients' chest and back to acquire lung sounds for detection of asthma. For analysis, they followed the single sensor based approach with the specific aim of wheeze detection as a probable cause of asthma in any one of the eight sensors. So far, the usefulness of channel (i.e., the lung sounds recording position over the lungs) combination study in asthma detection remains unexplored. There is a large number of asthma related analysis done using tracheal sounds [14–16,18,20,21] which are limited by lack of use of specific positional information related to the lungs. A few other works are found in the literature where changes in the posterior lung sounds are targeted rather than adventitious sound as a marker to diagnose the lung status [27–29].

In this work, we have classified normal and asthmatic subjects based on the alterations in their posterior lung sound signals irrespective of the presence of wheezing sound. We have used a novel 4-channel data acquisition system to acquire lung sounds from four different positions on the posterior chest of normal and asthmatic subjects, as shown in Fig. 1. The locations were suggested by the pulmonologist, and it provides less interference from the heart sounds during the lung sounds recording process. The proposed framework extracts features from the PSD of the lung sound signals by considering the distribution of power over various ranges of frequencies. A set of *statistical features* is derived from the decomposed subbands of PSD and fed into the ANN and SVM classifiers for classification purpose. The work also presents a study of the classification performances for all possible combinations of the channels.

The rest of the paper is organized as follows. The database description, 4-channel lung sound acquisition system, baseline methods and proposed method are discussed in Section 2. This section also includes the classification environment, used throughout the manuscript. Experimental results of the different studies are reported in Section 3. Section 4 discusses the key findings, limitations and future scopes of this work. Finally, conclusions are drawn in Section 5 by summarizing the contributions made in this study.

2. Methods

2.1. Lung sound signals acquisition

Lung sound signals were recorded at Institute of Pulmocare and Research (IPCR), Kolkata, India, after obtaining necessary ethical clearance and consent of individual subjects. The primary identification of asthma was made as per Global Initiative for Asthma (GINA) guideline [30]. Total 60 subjects participated in this study, in which 30 normal and 30 asthma (8 mild, 11 moderate, and 11 severe asthma) subjects were present. The anthropometric and spirometric characteristics of all the participants [31,32] are given in Table 1 after rounding up the numbers to the full numbers.

Lung sound signals are the filtered version of the breath sound signals because lungs and chest wall act acoustically as a low pass filter [33]. It makes the intensity and frequency range of the lung sound signals lower than signals from the trachea, but it has the potential to provide lung status specific information. Usually, doctors listen to the lung sounds from multiple positions, one after another for lung status detection. The simultaneous hearing is not possible in the human being; consequently, doctors have to remember the characteristics of each location and patients need multiple numbers of breathing maneuvers.

In this study, lung sounds were recorded from the posterior chest to minimize the interference with the heart sound signals for it being more convenient for data collection in comparison to the front chest. The signals were acquired simultaneously from four different positions on the posterior chest wall (Fig. 1(b)) of each subject in sitting position at relaxed state in a quiet room. Subjects were requested to breathe deeper than normal during the recording [34]. This was done under the supervision of a senior chest physician. The four positions of data collection were the apical (lower interscapular areas) and posterior basal segments (infrascapular/subscapular areas) of both the lower lobes. No subject was undressed, but was requested to remove back covers such as sweater or rug, if any.

The 4-channel data acquisition system (Fig. 1(a)) consisted of four dual head stethoscopes (MDF-747) attached with condenser microphone in the tube of each stethoscope. It was a customized device where microphone, amplifier, filter, and analog-to-digital converter were used as per the Computerized Respiratory Sound Analysis (CORSAs) guidelines [35,36]. Channels were numbered as 1, 2, 3, 4 for lung sounds collection positions: right apical, right posterior basal, left apical and left posterior basal, respectively, on the posterior chest as shown in Fig. 1(b). Anatomically, the sites numbered as 1 and 3 are the interscapular regions and they correspond to the apical segments of the lower lobes while the sites marked as 2 and 4 are anatomically described as the infrascapular/subscapular areas and they correspond to the posterior basal segments of the lower lobes [37]. Two elastic chest belts were used, following CORSAs guidelines [35], to keep the sensors attached to the body. A block diagram based representation of the entire system is shown in Fig. 2. The recorded lung sound signals were passed through an analog signal conditioning unit that amplified the signals and reduced the environmental noise by filtering. The output analog signals were converted into digital signals using external USB sound card (A/D converter) at a sampling frequency of 8 kHz. Digitized data was stored as .wav files in 16 bits, pulse code modulation, and mono audio format, in a digital computer through a USB hub for further processing. The total duration of the recording per subject was 45 s.

2.2. Preprocessing and lung sound cycle extraction

The acquired raw lung sound signals are digitally filtered using an IIR Butterworth band pass filter within the frequency range

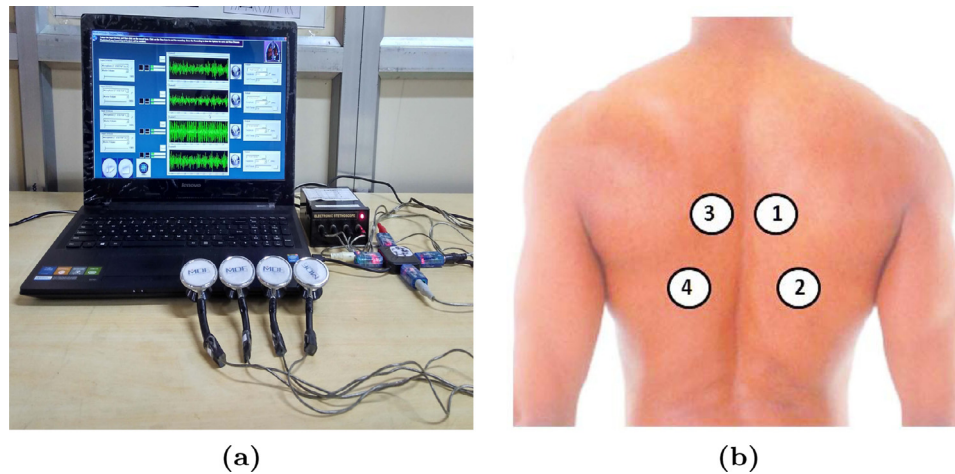


Fig. 1. (a) 4-channel data acquisition system and (b) lung sounds recording positions.

Table 1

Anthropometric and spirometric characteristics of the normal and asthmatic subjects.

Feature	Category	
	Normal	Asthma
Number of subjects	30 (20M, 10F)	30 (22M, 8F) Mild: 8 Moderate: 11 Severe: 11
Age (year) mean $\pm$ SD	33 $\pm$ 9	50 $\pm$ 18
BMI (kg/m ²) mean $\pm$ SD	24 $\pm$ 3	23 $\pm$ 4
FVC (l) mean $\pm$ SD	4 $\pm$ 1	3 $\pm$ 1
FVC (% of predicted) mean $\pm$ SD	89 $\pm$ 8	75 $\pm$ 20
FEV1 (l) mean $\pm$ SD	3 $\pm$ 1	2 $\pm$ 1
FEV1 (% of predicted) mean $\pm$ SD	89 $\pm$ 9	62 $\pm$ 21

Note: M: Male, F: Female, SD: Standard Deviation, BMI: Body Mass Index, FVC: Forced Vital Capacity, and FEV1: Forced Expiratory Volume in 1 s.

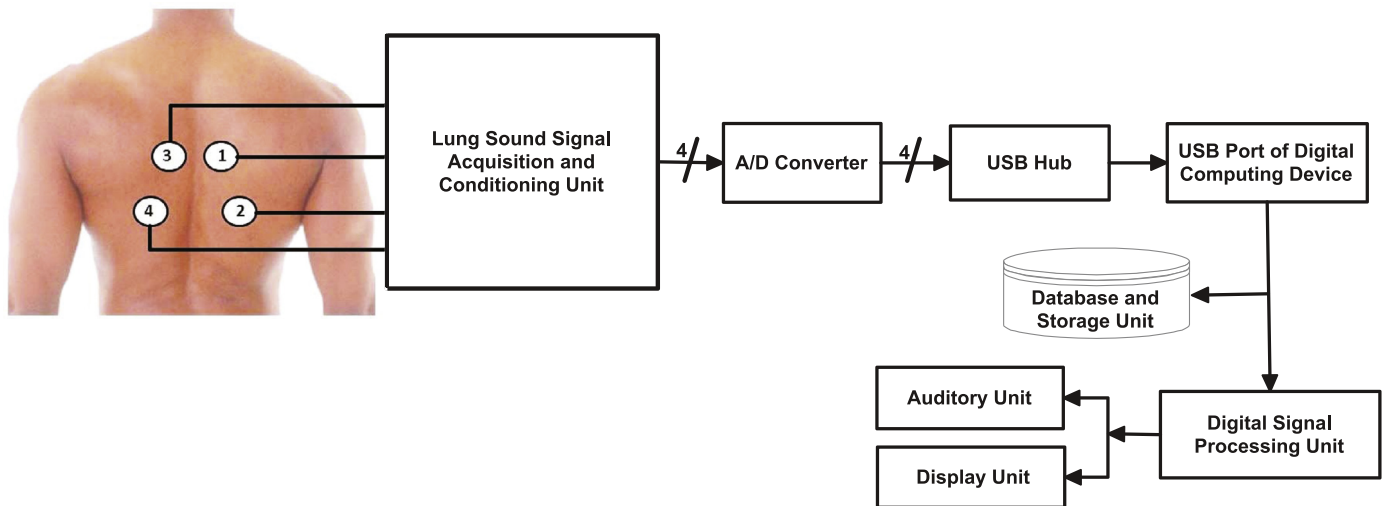


Fig. 2. Block diagram of the 4-channel data acquisition system.

from 70 to 2000 Hz to reduce the heart and muscle artifacts [38]. The band pass filtered signals are passed through four cascaded notch filters to remove the power line noise, where the bandwidths of the notch filters are kept as minimum as possible to reduce spectral loss [39].

Fig. 3 shows the lung sound signals before and after preprocessing of two randomly selected normal and asthmatic subjects. The preprocessed lung sound signals are amplitude normalized to limit the dynamic range of each signal between -1 and $+1$. The variation in amplitude is due to the factors such as physiology, age, and sex of the subjects. Amplitude normalization of a signal $X(n)$ is

done by dividing the entire signal by its maximum absolute value of the amplitude, as given in Eq. (1). Clinicians having expertise in auscultation observed distinct improvement in the audio quality of the preprocessed signal for its clinical use.

$$X(n)_{\text{norm}} = \frac{X(n)}{\max[\text{abs}(X(n))]} \quad (1)$$

where $n = 1, 2, \dots, K$, and K is the total number of samples in a lung sound signal.

It has been observed that a lung sound cycle consisting of an inspiration phase and an expiration phase, contains useful infor-

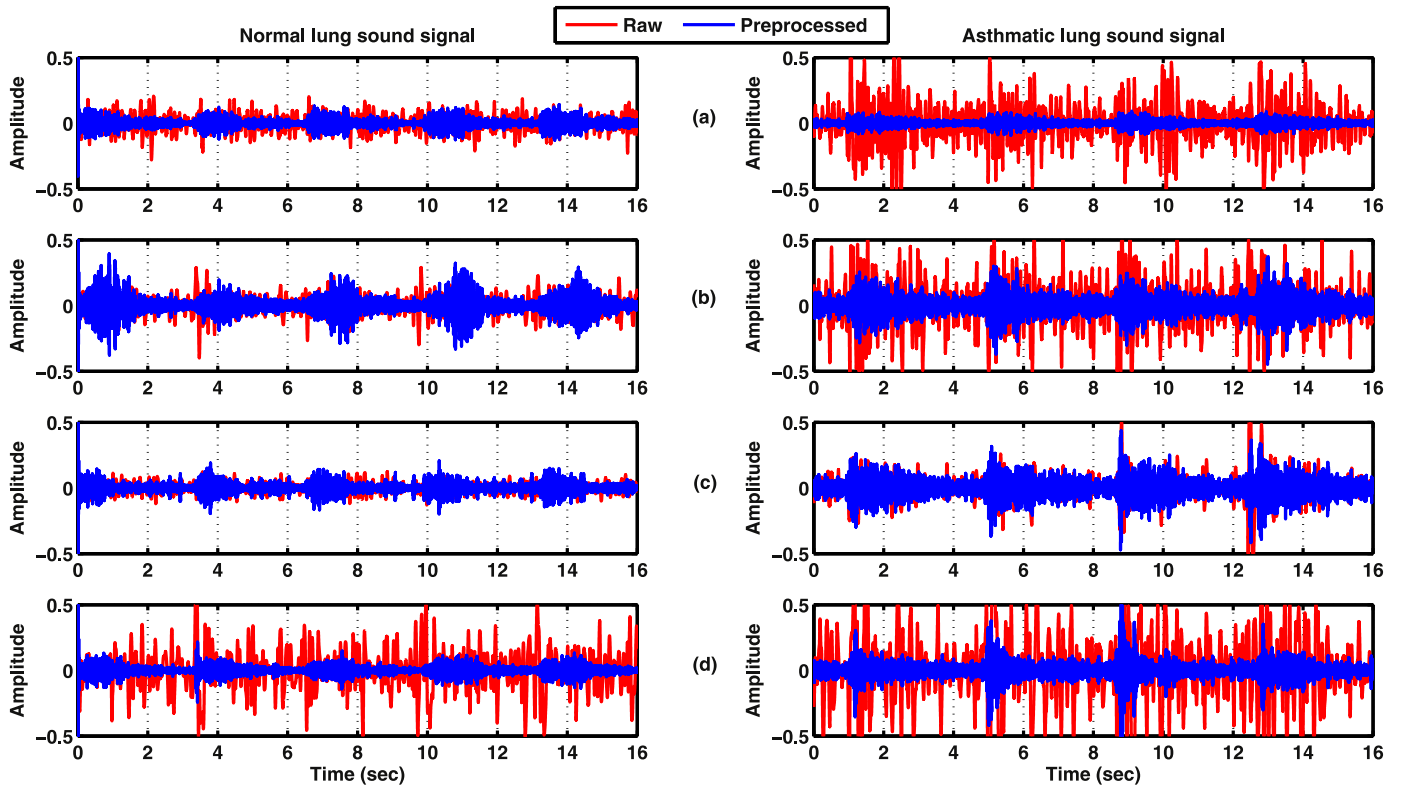


Fig. 3. Raw and preprocessed lung sound signals of a normal (left) and asthma (right) subjects from the posterior chest (a) right apical, (b) right posterior basal, (c) left apical and (d) left posterior basal segments of the lower lobes.

mation related to lung conditions [40]. We take one complete lung sound cycle from each channel of a subject to diagnose the lung status [11,17,40]. In this study, the lung sound cycles are extracted manually, by listening to and visualizing the signal in time and time-frequency domain. Wheezing sound is heard in 10 asthmatic subjects (high frequency wheezing in 8 subjects and low frequency wheezing in 2 subjects), and vesicular sound is heard in rest 20 asthmatic subjects and in all the normal subjects. Wheezing sound is heard in a few of the asthmatic subjects rather than all because it is not always present in active asthma or at the time of recording [26]. Four lung sound cycles are extracted from four channels of each subject at the same time frame. Total 240 lung sound cycles (30×4 normal and 30×4 asthma) from 60 subjects are taken into consideration for subsequent analysis. Lung sound cycles of two randomly selected normal and asthma subjects are shown in Fig. 4 for all four channels.

2.3. Baseline methods

Here, we describe three earlier used methods [14,17,41] of lung sounds classification. The work in [14,17,41] used single channel based system to collect lung sounds from the suprasternal notch, over the lungs, and six different positions on the posterior chest, respectively. All the baseline methods had recruited asthmatic subjects for data collection in their studies. The work in [14] had classified normal and asthmatic subjects wherein the work in [17] and the work in [41] had collected wheezes and rhonchus from asthmatic subjects, respectively for classification.

The work in [14], termed as Method-1 in this paper, estimates Welch's PSD for each lung sound cycle. The frequency range 100–1300 Hz is decomposed into 26 bands of approximately 46 Hz width. The average power of each subband is used as features to classify normal and asthma using ANN classifier. The feature vector

is formed as:

$$F_R = [\bar{P}_1, \bar{P}_2, \dots, \bar{P}_{26}]^T \quad (2)$$

where $\bar{P}_k$ is the average power of k th subband and T denotes transposition operator.

For Method-2 [17], the lung sound cycles are transformed into time-frequency representations using wavelet transform. In this, wavelet transform was applied up to 7th decomposition level, and statistical features such as (i) mean of the absolute values of the coefficients in each subband (μ_{d_k}), (ii) average power of the wavelet coefficients in each subband (P_{d_k}), (iii) standard deviation of the coefficients in each subband (σ_{d_k}) and (iv) ratio of the absolute mean values of adjacent subbands ($\mu_{d_k}/\mu_{d_{k+1}}$), were computed from d_3 , d_4 , d_5 , d_6 and d_7 subbands, which corresponds to the frequency range 43.07–1378.13 Hz. This method was proposed to classify respiratory sounds into one of these classes: normal, crackle, wheeze, stridor, squawk or rhonchus. In our work, the wavelet transform is also carried out up to 7th decomposition level. Statistical features are extracted from d_2 , d_3 , d_4 , d_5 and d_6 subbands (as our sampling frequency is 8 kHz) which corresponds to the frequency band 62.50–2000 Hz. Here, the feature vector can be represented as:

$$F_{W'} = [\mu_{d_k}, P_{d_k}, \sigma_{d_k}, \mu_{d_k}/\mu_{d_{k+1}}]^T; \quad k = 2, 3, \dots, 6 \quad (3)$$

The more recent Method-3 [41] uses four types of features extracted from the lung sound cycle, (i) frequency ratio ($f_{\min}/f_{\max}$) calculated from Welch's PSD, (ii) average instantaneous frequency (IF_{mean}) and (iii) exchange time of the instantaneous frequency (ET_{IF}) calculated by the Hilbert-Huang transform (HHT), and (iv) eigenvalues obtained from the singular spectrum analysis (SSA). This method was proposed to separate crackles and rhonchi (similar to wheezes and also difficult to distinguish from wheezes [17]) of pathological lung sounds from normal lung sounds.

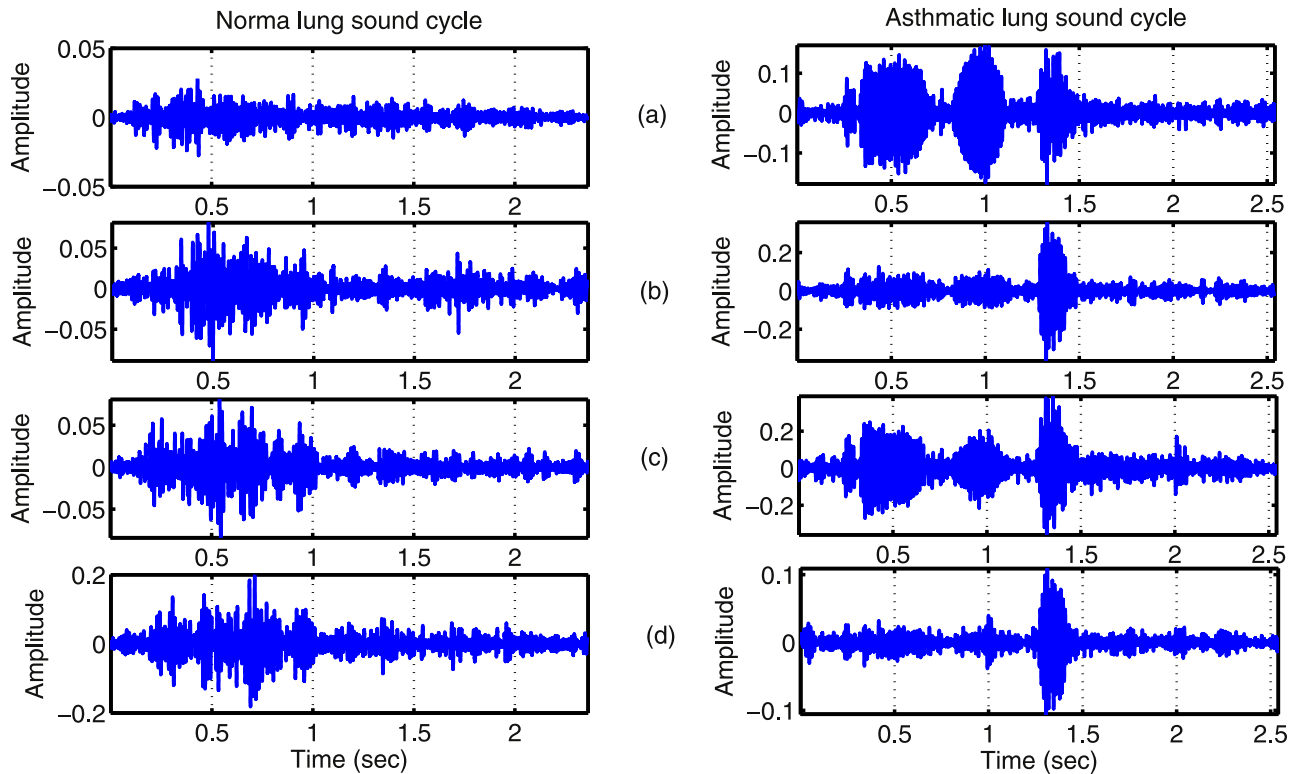


Fig. 4. Lung sound cycles of a normal (left) and asthma (right) subjects from the posterior chest of (a) right apical (b) right posterior basal (c) left apical and (d) left posterior basal segments of the lower lobes.

These baseline methods are implemented in our database to discriminate normal and asthmatic subjects using proposed 4-channel data acquisition framework. The purpose of this baseline study is to measure the effectiveness of the commonly used features in this field.

2.4. Proposed method

In this section, we propose a novel feature extraction technique to extract significant information from lung sounds of normal and asthmatic subjects.

2.4.1. Feature extraction

There are regional variations in the lung sounds intensity due to its non-uniform distribution over the lungs [33], so the acquisition of lung sounds from four different positions could be beneficial for understanding and analysis of normal and abnormal lung sounds. Moreover, bronchial obstruction in asthma causes an increase of high-frequency components of lung sounds spectrum even in absence of wheezing sound [42,43]. The median frequency of the lung sounds may be raised even if, there exists normal ventilatory function of an asthmatic subject [44]. There is also a probability that the allergic inflammation in the airways of asthmatic subjects may introduce certain modification in the mucosal and submucosal part of the bronchi; consequently, it can introduce alteration in the dynamics of the airflow, including turbulence, during the breathing maneuver [33]. Hence, the extraction of features from the frequency domain of the lung sound cycle can appreciate this information; consequently, we propose to compute four statistical features from the subbands of the PSDs to capture the changes in detail from posterior lung sound signals of normal and asthmatic subjects.

2.4.1.1. Power spectral density estimation using Welch's method. The feature extraction process of a lung sound cycle is shown in Fig. 5. Power spectral density (PSD) is estimated from each lung sound cycle using Welch's method [45]. This requires a choice of the window function, the width of the window and the amount of overlap between two consecutive segments. We have applied 1s window for better frequency resolution. Hanning window is used as it is a one of the preferred window that smoothen with an acceptable spectral leakage [46]. Fig. 6 shows the average PSD over all the subjects for each recording position where the distinction between the power distribution with respect to frequency is presented for both the classes. The power of the lung sounds depends on the volume of the air flow [47]. The maximum level of flow in a respiratory cycle tends to vary from subject to subject due to natural variation in breathing pattern, e.g., variation in respiration depth and frequency of respiration. Hence, each PSD is z-score normalized [15] to have zero mean and unit variance.

2.4.1.2. Division of PSD into subbands. The 70–1000 Hz frequency range of each PSD is divided into uniform subbands [14], e.g., for subband width of 40 Hz, the 70–1000 Hz frequency range is decomposed into 23 subbands such as 70–110 Hz, 110–150 Hz, 150–190 Hz, ..., 950–990 Hz, and features are extracted from these subbands.

2.4.1.3. Computation of statistical features. The box plot is a standardized way of displaying the distribution of the data. For better visualization, the z-scores of all 23 subbands (for 40 Hz subband width) of two randomly selected normal and asthmatic subjects are shown by box plots in Fig. 7 after unity-based normalization. In the box plot, 50% of the data lies in the box, middle line in red color represents the median of the data, and the vertical lines extending from the boxes (whiskers) indicate variability outside the upper and lower quartiles. If the notches of the two boxes do not

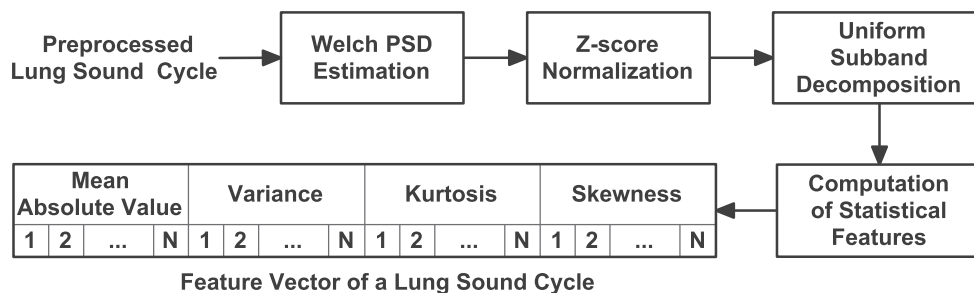


Fig. 5. Block diagram of the feature set formulation process of a lung sound cycle.

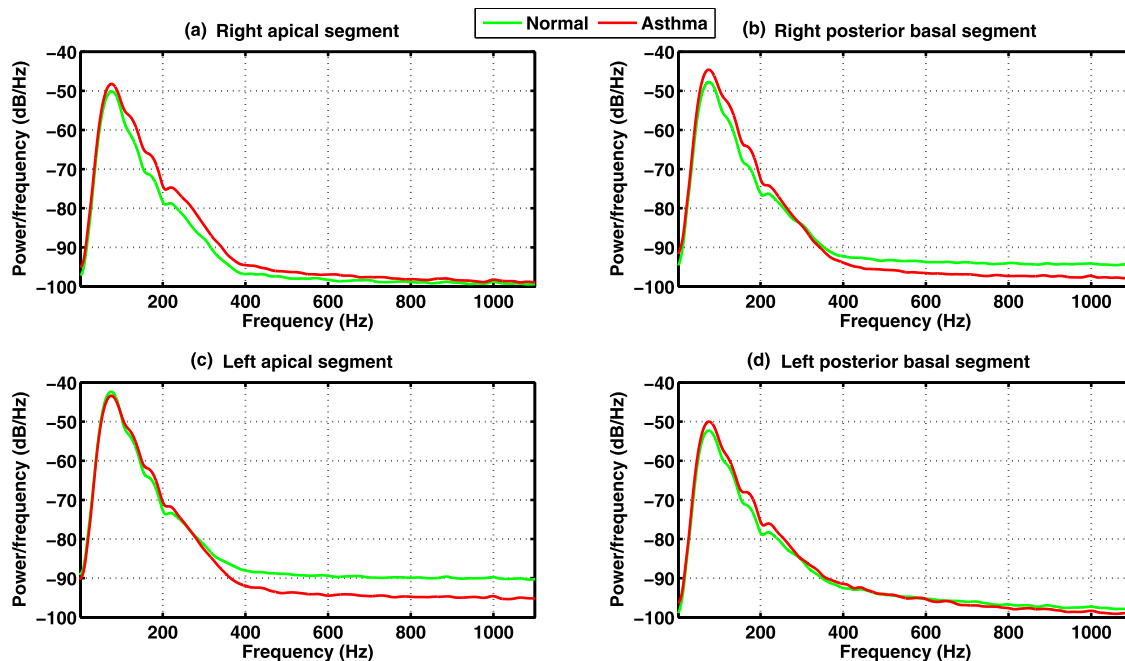


Fig. 6. Average PSD across all the subjects for each of the segments from lower lobes on the posterior chest.

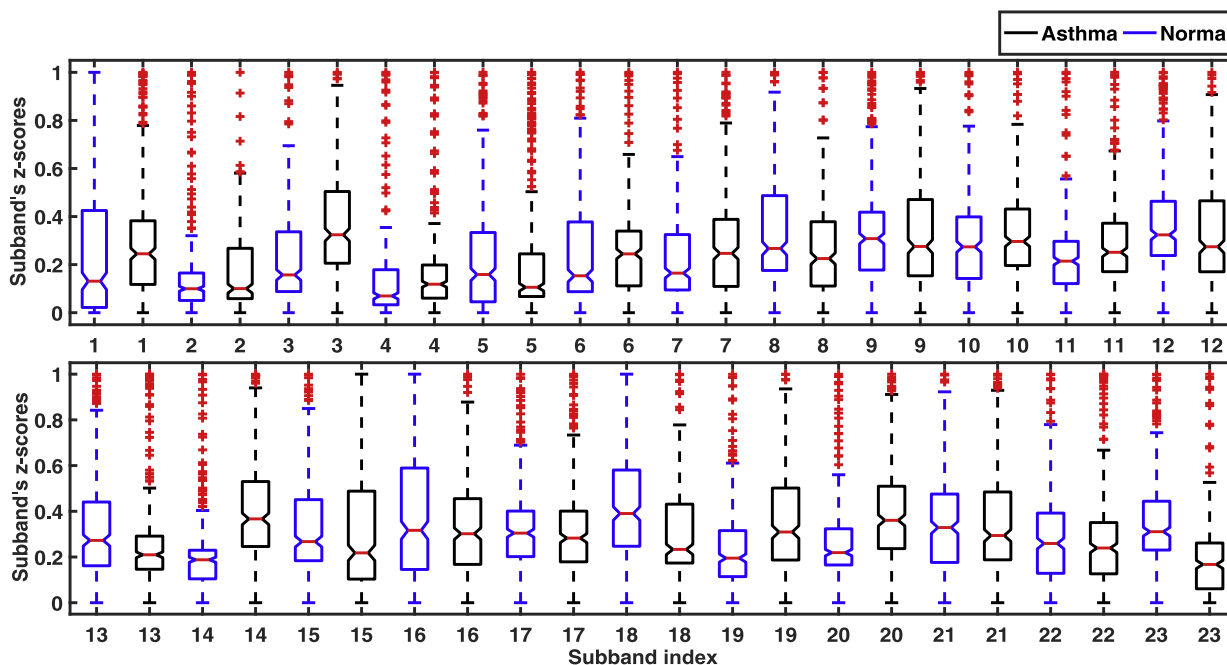


Fig. 7. The statistical comparison of the subbands from a normal and asthmatic subjects.

overlap then there is a strong evidence (95% confidence) that their medians differ [48]. From Fig. 7, we can find that distinction can be made between the two classes from the height of the box (indicates the spread/compactness of the data), location of the median in the box (indicates the skewness of the data), position of the notch in the box (confirms whether two medians differ or not), and the range of the z-scores (represents the variation in the data) in each of the box plots. Extending the findings of Fig. 7 to the dissimilarities noted over the frequency ranges of Fig. 6, we propose to extract following statistical features from each of the subbands:

- (i) Mean of the absolute values (MABP)

$$\text{MABP}^k = \frac{1}{M} \sum_{j=1}^M |Y_j^k| \quad (4)$$

- (ii) Variance (VAR)

$$\text{VAR}^k = \frac{1}{M} \sum_{j=1}^M (Y_j^k - \mu^k)^2 \quad (5)$$

- (iii) Kurtosis (KURT)

$$\text{KURT}^k = \frac{\frac{1}{M} \sum_{j=1}^M (Y_j^k - \mu^k)^4}{\left(\frac{1}{M} \sum_{j=1}^M (Y_j^k - \mu^k)^2 \right)^2} \quad (6)$$

- (iv) Skewness (SKEW)

$$\text{SKEW}^k = \frac{\frac{1}{M} \sum_{j=1}^M (Y_j^k - \mu^k)^3}{\left(\frac{1}{M} \sum_{j=1}^M (Y_j^k - \mu^k)^2 \right)^{3/2}} \quad (7)$$

where k denotes the k th subband and M denotes the total number of z-scores of a subband. Y_j^k is the j th z-score and μ^k is the mean of the z-scores in k th subband.

Note that, MABP measures intensity of a subband, VAR measures variation within it, KURT measures its flatness and SKEW measures the asymmetry in the distribution of the z-scores in a subband. Extracted features are concatenated to represent the characteristic feature vector of a single lung sound cycle for the corresponding channel. If N number of subbands are generated from the PSD of a lung sound cycle, then the feature vector of that cycle is constructed as shown in Fig. 5. Subsequently, the feature vectors obtained from all four channels are concatenated to represent the final feature vector of a subject when all the channels are taken together for analysis.

2.4.2. Feature selection

Feature selection helps in reducing computational load for real-time implementation and also for removing redundant information that can affect the modeling process. We perform Student's t -test on the training feature set to select the significant features [49]. Before applying Student's t -test, we have checked the normality of the features using histogram plot, normal probability plot, and also plotted the empirical cumulative distribution function (CDF) and the standard normal CDF for a visual comparison [50]. Furthermore, Kolmogorov–Smirnov one-sample [51] test has also been applied to check the normal distribution of the features, and it has been found that most of the features have followed normal distribution and very few features have slightly deviated from the normal distribution. But, the parametric tests such as the t -test, z -test, ANOVA are sufficiently robust that the modest deviations of the data from normality do not adversely affect the reliability of the test result [51]. The selected feature indices are used to take corresponding features from the test feature set. Finally, the selected training and testing feature sets are used for the classification of normal and asthmatic subjects.

2.4.3. Parameter selection using grid search process

The feature extraction and selection processes depend on the following parameters which may also affect the classification performance of normal and asthmatic subjects:

- (i) Percentage of overlap between two consecutive segments in Welch's PSD estimation
- (ii) Width of the subband in subband breaking stage
- (iii) Significance level (α) in Student's t -test for feature selection

We apply the grid search process to get the optimum parameter set, and to achieve the best classification performance of normal and asthmatic subjects. Here, the grid search is an approach to find out the optimum set of the above-mentioned parameters by searching all possible combinations of the parameters on the defined search space. In this work, the percentage of overlap is varied from 0 to 90% with step size 10%, subband width is varied from 10 to 100 Hz with step size 10 Hz, and significance level (α) is varied from 0.005 to 0.05 with step size 0.005.

2.4.4. Classifiers and performance evaluation metrics

Artificial neural network (ANN) and support vector machine (SVM) classifiers are widely used in biomedical field for classification of different diseases [10,52–54]. ANN classifier performs non-linear mapping of the inputs to the outputs for classification of data into different classes [55]. SVM classifier separates the data of different classes by constructing an optimal hyperplane with the biggest possible margin [56]. The margin is defined as the distance between optimal hyperplane and a vector which lies closest to it. In this work, Artificial neural network (ANN) with three layers (i.e., one input, one hidden and one output layer) is used [17]. ANN is trained by using scaled conjugate gradient backpropagation algorithm [17,57]. We use a static structure of the hidden layer by considering the number of hidden nodes is 10 for all combinations of the parameters. Whereas for implementation of the SVM classifier, LIBSVM is used as suggested in [58] with linear kernel function and default value of the penalty parameter 'C' for the classification of normal and asthmatic subjects.

The validation procedure of [20] has been followed throughout this manuscript. We have used 58 subjects (29 normal and 29 asthma) in training and the remaining two subjects (1 normal and 1 asthma) in testing in each time. When n th indexed subjects from normal and from asthma are tested ($n \leq 30$), then subjects with indices [1 to ($n - 1$) and ($n + 1$) to 30] of normal and of asthma are used in training. This is repeated for each subject (leave-one-out method [20]), i.e., total 30 times repeated to test all the 60 subjects. This whole classification method is iterated 25 times (i.e., testing of all the 60 subjects represents one iteration) [17,21] to address the random initialization related aspect of a classifier, and the average performance has been reported.

The performance of each test is characterized in terms of its ability to identify true positives while rejecting false positives [59]. Three commonly used metrics for performance evaluation of the classifier: sensitivity (SEN), specificity (SPE) and accuracy (ACC) are used throughout this manuscript. They are defined as follows:

- Sensitivity (SEN) is defined as the probability that an asthma subject is classified in the class asthma.
 $\text{SEN} = \text{TP}/(\text{TP} + \text{FN})$
- Specificity (SPE) is defined as the probability that a normal subject is classified in the class normal.
 $\text{SPE} = \text{TN}/(\text{TN} + \text{FP})$
- Accuracy (ACC) is defined by the ratio of the true detection of normal and asthma subjects to the total number of subjects.
 $\text{ACC} = \text{SEN} \times \text{P(A)} + \text{SPE} \times \text{P(N)} = (\text{SEN} + \text{SPE})/2$

where TP, TN, FP, and FN indicates true positive, true negative, false positive and false negative test results, respectively. P(A) and P(N)

are the fractions of the total subjects that are asthma and normal respectively, and the value of P(A) and P(N) is 1/2 due to the equal number of subjects in each class. To measure the reliability of the average classification accuracy, standard error (SE) [60] has been computed from each iteration and the mean standard error of 25 iterations has been reported along with the mean accuracy for proposed and baseline methods. Classification accuracies are reported in the text as ACC($\pm$ SE)% throughout the manuscript. Moreover, we have also calculated another performance measurement metric, i.e., the predictive value, and given it in the [Appendix A](#).

2.5. Hardware and software specifications

All the algorithms are implemented on Matlab (version 2013a) programming language. The experiments are conducted in a Lenovo (system model: 10ASA00RIH) desktop computer using Intel(R) Core(TM) i5-4570S CPU @ 2.90 GHz, 8GB RAM and Windows 7 operating system.

3. Results

In this section, we present the results of different experiments carried out using 4-channel lung sound signals. At first, we describe the performances of the baseline methods in the multichannel framework. Next, the performances of the proposed method for each individual channel and four channels taken together are presented. Finally, the performance of the channel combination study is depicted.

3.1. Performances of the baseline methods

We have implemented three baseline methods [14,17,41] in multichannel environment to investigate the efficacy of their features. In case of analysis of four channels together, the feature vectors of four individual channels are concatenated to represent the final feature vector. The work in [14,17,41] used ANN, ANN, and SVM classifiers for Method 1, 2, and 3, respectively. We extend that work in this paper and include both types of classifiers, i.e., ANN and SVM, for classification of normal and asthma in our database. For each baseline method, the classification performances have been evaluated in two different classifiers, i.e., one classifier with the same settings as used in the corresponding baseline method and another classifier with the same settings as used in the proposed method. Classification performances of the baseline methods are presented in [Table 2](#) where Method 3 achieves maximum performance among all the three baseline methods. The performance is degraded in Method 2 and Method 3 when all the channels are taken together for analysis.

3.2. Performance of the proposed method

3.2.1. Performances of each individual channel and four channels together

We have applied the grid search process to each individual channel separately and, for four channels together to find out the corresponding optimum parameter set. The best classification performances in terms of accuracy, sensitivity, and specificity, obtained from grid search process are reported in [Table 3](#). It is observed from [Table 3](#) that SVM yields better classification performance as compared to ANN for each individual channel (as obtained from the McNemar's test [20] at the significance level $\alpha = 0.05$). Maximum classification performance is obtained from channel 2 (right posterior basal segment) among all the individual channels for both the classifiers. When all the channels are combined, it outperforms the best individual channel performance for

Table 2
Lung sounds classification performances of the baseline methods in the multichannel framework.

Method	Feature	Classifier	Channel-1				Channel-2				Channel-3				Channel-4				All channels			
			ACC (%) (±SE%)	SEN (%)	SPE (%)	ACC (%) (±SE%)	ACC (%) (±SE%)	SEN (%)	SPE (%)	ACC (%) (±SE%)	ACC (%) (±SE%)	SEN (%)	SPE (%)	ACC (%) (±SE%)	ACC (%) (±SE%)	SEN (%)	SPE (%)	ACC (%) (±SE%)	ACC (%) (±SE%)	SEN (%)	SPE (%)	
Method-1	Average power	SVM	63.3 (5.23)	40.0	86.7	60.0 (5.47)	76.7	43.3	68.3 (6.86)	66.7	70.0	48.3 (6.00)	56.7	40.0	75.0 (6.12)	73.3	76.7					
		ANN	59.6 (5.38)	54.0	65.2	62.8 (6.34)	57.3	68.3	60.7 (5.79)	54.4	67.1	59.5 (6.34)	56.7	62.3	69.6 (5.40)	68.4	70.8					
Method-2	Composite	SVM	65.0 (4.80)	33.3	96.7	71.7 (5.10)	86.7	56.7	65.0 (5.84)	76.7	53.3	53.3	66.7	60.0	66.7 (4.90)	70.0	63.3					
		ANN	50.9 (6.36)	49.2	52.7	61.7 (5.65)	60.1	63.2	56.2 (6.05)	54.8	57.6	58.6 (6.09)	54.7	62.5	61.3 (5.67)	64.4	58.1					
Method-3	$f_{\min}/f_{\max}$	SVM	60.0 (4.34)	33.3	86.7	45.0 (4.91)	36.7	53.3	63.3 (6.63)	63.3	63.3	45.0 (3.61)	16.7	73.3	50.0 (6.66)	50.0	50.0					
		ANN	51.1 (5.43)	38.7	63.5	64.1 (6.22)	61.6	66.7	55.7 (5.39)	57.7	53.7	31.9 (4.86)	30.9	32.9	48.3 (6.40)	42.1	54.4					
	I_{mean}	SVM	63.3 (6.20)	43.3	83.3	75.0 (5.13)	83.3	66.7	65.0 (5.84)	76.7	53.3	58.3 (6.27)	73.3	43.3	63.3 (6.20)	66.7	60.0					
		ANN	56.4 (6.11)	44.7	68.1	82.3 (4.33)	81.7	82.9	60.3 (5.43)	64.0	56.7	46.0 (5.58)	45.1	46.9	64.9 (5.70)	68.5	61.2					
	ET_{IF}	SVM	56.7 (3.89)	20.0	93.3	55.0 (4.31)	16.7	93.3	38.3 (3.86)	73.3	63.3	51.7 (1.63)	100.0	63.3	53.3 (6.20)	33.3	73.3					
		ANN	49.3 (6.57)	40.1	58.5	56.6 (4.97)	25.7	87.5	39.5 (6.03)	53.6	25.3	53.1 (6.02)	37.3	68.8	44.7 (6.30)	40.1	49.2					
	Eigenvalues	SVM	66.7 (5.44)	43.3	90.0	53.3 (6.63)	43.3	63.3	70.0 (5.05)	80.0	60.0	31.7 (4.99)	26.7	36.7	68.3 (6.00)	83.3	53.3					
		ANN	52.7 (6.63)	47.6	57.9	44.7 (6.36)	38.4	51.1	56.0 (5.51)	51.3	60.7	47.8 (6.13)	47.2	48.4	51.3 (6.53)	50.0	52.5					

Notes: Composite means all extracted features of Method-2 are together. The maximum classification accuracy (ACC (%)) and its corresponding sensitivity (SEN (%)) and Specificity (SPE (%)) are kept bold for each individual channel and for all channels.

Table 3

Lung sounds classification performances (best from grid search process) of the proposed method for each individual channel and 4-channel taken together.

Channel	Classifier	Parameter			Average feature dimension	Classification performance		
		Overlap (%)	Subband width (Hz)	Significance level (α)		ACC (%) ($\pm$ SE%)	SEN (%)	SPE (%)
1*	SVM	90	30	0.025	31	80.0 (5.05)	80.0	80.0
	ANN	90	50	0.015	16	77.7 (5.49)	79.3	76.1
2*	SVM	50	30	0.04	31	86.7 (4.67)	90.0	83.3
	ANN	20	100	0.02	12	81.5 (4.96)	87.2	75.9
3*	SVM	70	10	0.035	93	80.0 (6.05)	76.7	83.3
	ANN	90	10	0.01	80	74.9 (5.12)	76.1	73.6
4*	SVM	0	10	0.045	23	81.7 (4.99)	80.0	83.3
	ANN	0	10	0.045	23	75.3 (5.41)	78.0	72.5
All	SVM	90	30	0.02	81	88.3 (3.86)	90.0	86.7
	ANN	50	30	0.045	110	86.1 (4.11)	88.3	84.0

Notes: * denotes that the classification performances of SVM and ANN classifiers are statistically significant as per the McNemar's test at the significance level $\alpha = 0.05$.

The row corresponding to the maximum classification accuracy (ACC (%)) is kept bold.

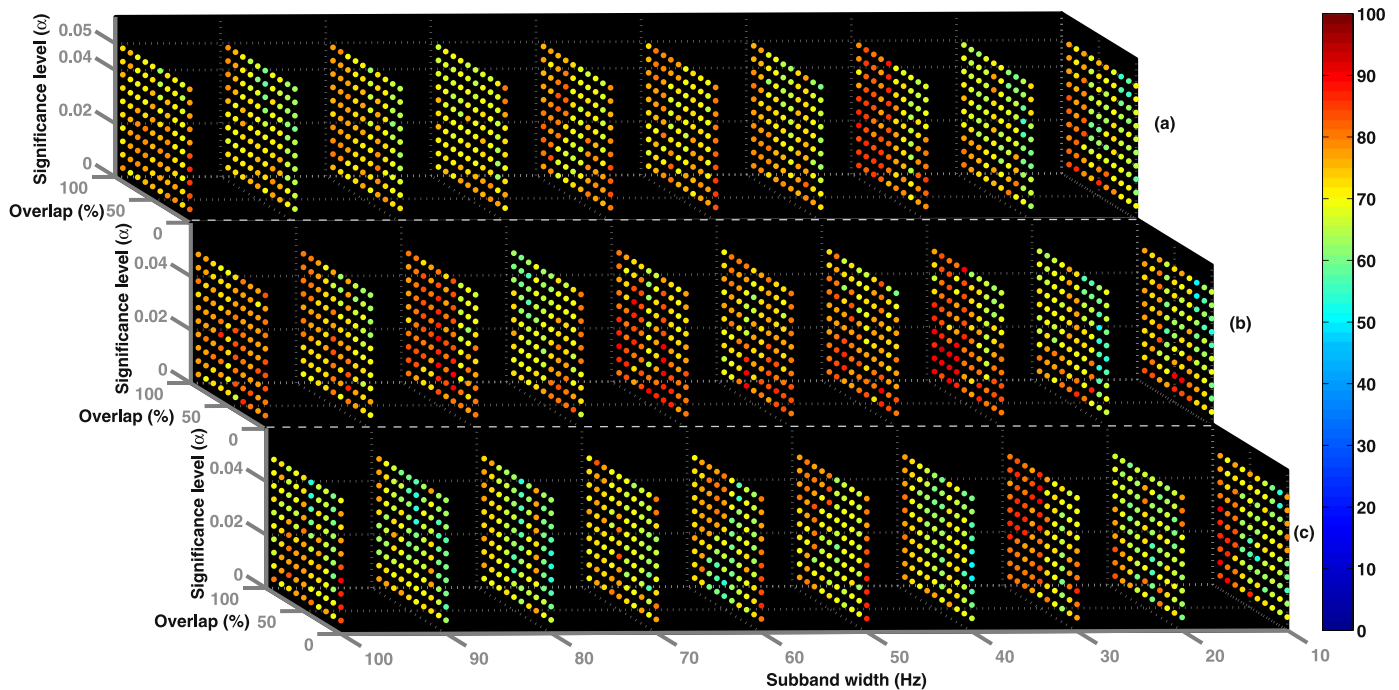


Fig. 8. Grid search performance of the proposed method for four channels taken together in SVM classifier on 3D space where (a) accuracy, (b) sensitivity, and (c) specificity are presented for all possible combinations of the parameters. Color bar represents the level of performance in terms of intensity.

both the classifiers. The classification performances of four channels together, obtained from grid search process are shown in Fig. 8.

3.2.2. Performance of the channel combination study

Earlier, most of the respiratory sound analysis works were done using single channel data acquisition system. In asthma, the airways are mainly affected, and the amount of blockage in the airways depends upon the severity of the obstruction and phenomenon like mucus plugging. The quantity of blockage in the airways is different at different portions of the lungs. Therefore, a multichannel lung sound signal acquisition system is expected to be more useful. However, there is a scope to study if specific channel combinations can give better result by removing redundant information, if any. In this study, we investigate the performances of all possible combinations of the recording locations to analyze how they are useful in distinguishing normal and asthmatic subjects. We use proposed subband based statistical features for this study. The best classification performances considering all possible channel combinations, obtained from the grid search processes

are shown in Table 4. The maximum classification performance is achieved for the 3-channel combination of 1, 2, and 4 channels.

4. Discussion

In this work, we have implemented three baseline methods in multichannel environment on our 4-channel database to know the effectiveness of the commonly used features that helped us to frame the proposed method. Next, the proposed method is implemented for each individual channel separately, and then for four channels together. A channel combination study has also been presented using proposed method to investigate the best possible combination of the channels/positions for classification of normal and asthmatic subjects.

It has been observed from Table 2 that average instantaneous frequency (IF_{mean}) of Method 3 gives superior performance compared to others. The possible reason is that the bronchial obstruction and allergic inflammation in the airways introduce alterations in the airflow and turbulence of asthmatic subjects [33,42–44] that lead to change in frequency pattern of the lung sound signal during

Table 4

Lung sounds classification performances (best from grid search process) of the proposed method for all possible combinations of the recording locations.

Channel combination	Classifier	Parameter			Average feature dimension	Classification performance		
		Overlap (%)	Subband width (Hz)	Significance level (α)		ACC (%) ($\pm$ SE%)	SEN (%)	SPE (%)
[1, 2]	SVM	90	30	0.005	37	90.0 (3.65)	93.3	86.7
	ANN	90	30	0.005	37	85.8 (4.18)	85.3	86.3
[1, 3]	SVM	90	10	0.04	184	83.3 (4.90)	83.3	83.3
	ANN	70	10	0.04	183	81.3 (5.19)	80.3	82.3
[1, 4]	SVM	90	10	0.005	76	83.3 (4.30)	73.3	93.3
	ANN	80	10	0.01	78	89.2 (3.87)	85.7	92.7
[2, 3]	SVM	0	50	0.01	31	85.0 (5.34)	86.7	83.3
	ANN	80	100	0.005	10	84.8 (4.37)	86.8	82.8
[2, 4]	SVM	30	40	0.01	26	85.0 (4.80)	90.0	80.0
	ANN	90	30	0.02	21	81.9 (4.45)	84.5	79.3
[3, 4]	SVM	80	10	0.01	84	85.0 (4.80)	83.3	86.7
	ANN	80	10	0.01	84	82.1 (5.24)	80.1	84.0
[1, 2, 4]	SVM	50	30	0.04	67	93.3 (3.10)	93.3	93.3
	ANN	50	30	0.045	70	87.3 (3.96)	92.1	82.4
[1, 2, 3]	SVM	50	30	0.035	97	90.0 (3.65)	86.7	93.3
	ANN	80	30	0.05	111	86.4 (4.15)	88.5	84.3
[2, 3, 4]	SVM	90	10	0.005	100	88.3 (3.86)	83.3	93.3
	ANN	90	10	0.005	100	83.7 (4.36)	79.5	88.0
[1, 3, 4]	SVM	90	10	0.005	153	83.3 (4.90)	73.3	93.3
	ANN	80	10	0.025	178	84.3 (5.13)	84.3	84.3

Notes: The row corresponding to the maximum classification accuracy (ACC (%)) is kept bold.

the breathing maneuver. The IF_{mean} feature captures these changes in a better way that provides better classification performance. Wavelet based features of Method 2 are not able to capture the distinguishable information due to the less number of subbands from the analysis frequency zone; consequently, it fails to capture the detailed information from normal and asthmatic lung sound cycles simultaneously. Hence, a relatively large imbalance between sensitivity and specificity is observed that gives poor performances in Method 2. Method 1 only gives better classification performance when all the channels are combined. The complementary information of the four different channels lifts up the performance compared to individual channel case. Hence, this subband based feature extraction technique has been adopted to design the proposed method with a few additional modifications.

In the proposed method, the classification performance for four channels taken together is significantly improved compared to the individual best performance. Since the combination of all the channels provides information of four different recording locations over the lungs at a time, the performance is improved for combined channel case than individual channel cases. We have also observed the following phenomena during the grid search process: (a) classification performances are found reasonable beyond 50% overlap due to a reduction of the spectral variance with increasing overlap [45] and (b) subband width between 10 and 50 Hz produces better results on the 3-dimensional (3D) search space (3D search space is constructed by plotting three different parameters in three different axes and performances using colors, as shown in Fig. 8) for its ability of capturing more detailed information from the PSD of the lung sound cycle.

Here, we compare the classification performances of baseline and proposed methods. The best classification accuracies of the baseline methods obtained from Table 2 are 66.7($\pm$ 5.44)% and 70.0($\pm$ 5.05)% for channel 1 and channel 3 by Method 3 [41] (eigenvalues), respectively, 82.3($\pm$ 4.33)% for channel 2 by Method 3 (IF_{mean}), 63.3($\pm$ 5.23)% for channel 4 by Method 2 [17], and 75.0($\pm$ 6.12)% for all channels together by Method 1 [14]. It has also been observed from Table 3 that the proposed method has outperformed the best accuracies of the baseline methods with the relative improvement of 13.3%, 4.4%, 10.0%, 18.4%, and 13.3% for channel 1, 2, 3, 4, and for all channels together, respectively. The proposed subband based feature extraction technique has been

found promising for its ability of capturing more delineated information from the PSD of the lung sound cycle. A better balance between sensitivity and specificity is also preserved in the proposed method which is absent in case of the baseline methods.

The channel combination study has helped us to appreciate the contribution of each recording location in the combined scenario. It is observed from Table 4 that the integration of apical and posterior basal segments (channel combination [1, 2] in SVM and [1, 4] in ANN classifiers in Table 4) yields superior performance. The movements of the lungs in the apical and basal regions are different that provides complementary information when both the areas are combined, and achieves better performance compared to other 2-channel combinations. The presence of signals from posterior basal segments (channel combination [2, 4]) outperforms the combination of the apical segments (channel combination [1, 3]) in both the classifiers (improvement in ANN classifier is minimal), which could be attributed to posterior basal segments representing larger area than the apical segments and providing more useful information. In 3-channel combinations, accuracy and specificity are improved significantly from the best performances of individual channels for both the classifiers. In SVM classifier, the combination of channel 1, 2, and 4 outperforms all the other combinations in Table 4 for both the classifiers. Channel 2 gives better sensitivity throughout the grid search space and the combination of channel 1 and 4 improves the specificity. The channel combination of 1, 2 and 4 gives best sensitivity (93.3%), specificity (93.3%) and accuracy (93.3($\pm$ 3.10)%) as compared to all other combinations. The probable physiological reason behind this is that the fusion of posterior basal segments along with the right apical segment covers a large area for data acquisition and provides nominal interference of the heart sound signal. Now, if we compare Tables 3 and 4, we can see that the performance is degraded when all the channels are taken in a combination (four channels together) in both the classifiers. Table 3 shows that the parameters set of each individual channel (i.e., the parameters set for which they achieved maximum classification performance in the grid search space) is different from others. But, in case of the grid search process of all channels together, same parameters are used for all the channels at a time and that could be a reason of performance impairment. Therefore, in future study, there is a scope to investigate the reason behind this performance deterioration of all channels together in a larger dataset. It

has also been observed that the classification performance has improved in each of the steps while moving from single to 2-channel and then 3-channel combinations for SVM classifier.

In this work, we did not consider lung sounds corresponding to the upper lobes as the movement of the lungs is restricted mostly towards the apices. In the future study, lung sounds from both the lobes, i.e., upper and lower lobes, can be taken into consideration by devising a suitable mechanism. In the collected database, considerable differences in the baseline characteristics such as age, FVC, and FEV1 can be found between the normal and asthmatic groups. It is to be noted here that the difference in the mean age is not expected to affect the quality of lung sound as it is age-independent in adults. The differences in lung function parameters (FVC, FEV1) are also natural since the diseased subjects are likely to have reduced functional capacity. However, in future, a study on the effect of difference in the mean age can be conducted by selecting number of subjects in each group appropriately. Furthermore, we have not considered other lung diseases in this paradigm, but in clinical practice other diseases could be present with different distribution. Therefore, the performance of the proposed system may decrease in a clinical setting where different diseases are present. Accordingly, we have also carried out a study for this to find out the effectiveness of the proposed method in detecting asthma in the presence of another lung disease. We did this by including chronic obstructive pulmonary disease (COPD) subjects in the asthma detection task. In this, we added 15 COPD subjects with 15 normal subjects and considered it as a single class, whereas the 30 asthmatic subjects are considered as another class. The classification performance of this experiment using the proposed features and all channels taken together showed sensitivity, specificity, and accuracy of 70.0%, 76.7%, and 73.3(± 5.71)%, respectively in SVM classifier, and 75.9%, 78.1%, and 77.0(± 5.43)%, respectively in ANN classifier. It is to be noted that we have not performed any additional feature level study to discriminate asthma against such a lung disease. Hence, in the future other lung diseases could be included in the paradigm to increase the robustness of the proposed asthma detection system; moreover, a multiclass lung disease detection system could be a future scope of this work.

5. Conclusions

In this paper, we have classified normal and asthmatic subjects using their posterior lung sound signals, recorded with the help of a novel 4-channel data acquisition system. We have analyzed lung sound signals of the posterior chest for the minimal interference of the heart sounds, which provides a better appreciation

of the respiratory system. We have used whole information of a lung sound cycle for classification purpose with the uniqueness of wheezing sound not being a necessary requirement for asthma detection. Therefore, this classification system can work for a larger range of asthmatic subjects. The channel combination study has shown how the different combinations of the segments on the lower lobes provide complementary information to improve the overall performance. A set of subband based statistical features is proposed in this work. The proposed features and its derivatives can also be exploited for the analysis of other obstructive and restrictive lung diseases, e.g., Chronic Obstructive Pulmonary Disease (COPD), Bronchiectasis and Interstitial Lung Disease (ILD).

Conflict of interest

None declared.

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Appendix A. Predictive value

The predictive values are calculated for proposed method, as well as for baseline methods. Predictive value has two metrics: (i) positive predictive value (PPV) and (ii) negative predictive value (NPV) [61]. They are defined as follows:

- Positive predictive value (PPV) is the percentage of the patients with a positive test who actually have the disease.

$$PPV = TP / (TP + FP)$$
- Negative predictive value (NPV) is the percentage of the patients with a negative test who do not have the disease.

$$NPV = TN / (FN + TN)$$

where TP, TN, FP, and FN indicates true positive, true negative, false positive and false negative test results, respectively. Table A.5 shows the predictive values of the baseline methods, and Tables A.6 and A.7 show the predictive values of the proposed method.

Table A.5

Lung sounds classification predictive values of the baseline methods in the multichannel framework.

Method	Feature	Classifier	Channel-1		Channel-2		Channel-3		Channel-4		All channels	
			PPV (%)	NPV (%)	PPV (%)	NPV (%)	PPV (%)	NPV (%)	PPV (%)	NPV (%)	PPV (%)	NPV (%)
Method-1	Average power	SVM	75.0	59.1	57.5	65.0	69.0	67.7	48.6	48.0	75.9	74.2
		ANN	60.8	58.6	64.4	61.5	62.3	59.5	60.0	59.0	70.1	69.1
Method-2	Composite	SVM	90.9	59.2	66.7	81.0	62.2	69.6	62.5	64.3	65.6	67.8
		ANN	51.0	50.9	62.0	61.3	56.4	56.0	59.3	58.0	60.6	62.0
Method-3	f_{min}/f_{max}	SVM	71.4	56.5	44.0	45.7	63.3	63.3	38.5	46.8	50.0	50.0
		ANN	51.4	50.8	64.9	63.4	55.5	56.0	31.6	32.3	48.0	48.5
	IF_{mean}	SVM	72.2	59.5	71.4	80.0	62.2	69.6	56.4	61.9	62.5	64.3
		ANN	58.4	55.2	82.7	81.9	59.6	61.2	45.9	46.1	63.8	66.0
	ET_{IF}	SVM	75.0	53.8	71.4	52.8	43.1	11.1	50.8	100.0	55.6	52.4
		ANN	49.2	49.4	67.3	54.1	41.8	35.3	54.5	52.3	44.1	45.1
	Eigenvalues	SVM	81.2	61.4	54.2	52.8	66.7	75.0	29.6	33.3	64.1	76.2
		ANN	53.0	52.5	44.0	45.3	56.6	55.5	47.8	47.8	51.3	51.2

Notes: Composite means all extracted features of Method-2 are together. PPV: Positive Predictive Value, NPV: Negative Predictive Value. The maximum predictive values are kept bold for each individual channel and for all channels.

Table A.6

Lung sounds classification predictive values (best from grid search process) of the proposed method for each individual channel and 4-channel taken together.

Channel	Classifier	Parameter			Average feature dimension	Predictive value (%)	
		Overlap (%)	Subband width (Hz)	Significance level (α)		PPV	NPV
1	SVM	90	30	0.025	31	80.0	80.0
	ANN	90	50	0.015	16	76.9	78.7
2	SVM	50	30	0.04	31	84.4	89.3
	ANN	20	100	0.02	12	78.3	85.6
3	SVM	70	10	0.035	93	82.1	78.1
	ANN	90	10	0.01	80	74.3	75.5
4	SVM	0	10	0.045	23	82.8	80.6
	ANN	0	10	0.045	23	74.0	76.7
All	SVM	90	30	0.02	81	87.1	89.7
	ANN	50	30	0.045	110	84.7	87.7

Notes: PPV: Positive Predictive Value, NPV: Negative Predictive Value.

The row corresponding to the maximum predictive values (both PPV (%) and NPV (%)) is kept bold.

Table A.7

Lung sounds classification predictive values (best from grid search process) of the proposed method for all possible combinations of the recording locations.

Channel combination	Classifier	Parameter			Average feature dimension	Predictive value (%)	
		Overlap (%)	Subband width (Hz)	Significance level (α)		PPV	NPV
[1, 2]	SVM	90	30	0.005	37	87.5	92.8
	ANN	90	30	0.005	37	86.1	85.5
[1, 3]	SVM	90	10	0.04	184	83.3	83.3
	ANN	70	10	0.04	183	81.9	80.7
[1, 4]	SVM	90	10	0.005	76	91.7	77.8
	ANN	80	10	0.01	78	92.1	86.7
[2, 3]	SVM	0	50	0.01	31	83.9	86.2
	ANN	80	100	0.005	10	83.5	86.3
[2, 4]	SVM	30	40	0.01	26	81.8	88.9
	ANN	90	30	0.02	21	80.4	83.7
[3, 4]	SVM	80	10	0.01	84	86.2	83.9
	ANN	80	10	0.01	84	83.4	80.9
[1, 2, 4]	SVM	50	30	0.04	67	93.3	93.3
	ANN	50	30	0.045	70	84.0	91.3
[1, 2, 3]	SVM	50	30	0.035	97	92.9	87.5
	ANN	80	30	0.05	111	84.9	88.0
[2, 3, 4]	SVM	90	10	0.005	100	92.6	84.8
	ANN	90	10	0.005	100	86.9	81.1
[1, 3, 4]	SVM	90	10	0.005	153	91.7	77.8
	ANN	80	10	0.025	178	84.3	84.3

Notes: PPV: Positive Predictive Value, NPV: Negative Predictive Value.

The row corresponding to the maximum predictive values (both PPV (%) and NPV (%)) is kept bold.

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