An Automated Lung Sound Preprocessing and Classification System Based OnSpectral Analysis Methods

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Abstract

In this work, respiratory sounds are classified into four classes in the presence of various noises (talking, coughing, motion artefacts, heart and intestinal sounds) using support vector machine classifier with radial basis function kernel. The four classes can be listed as normal, wheeze, crackle and crackle plus wheeze. Crackle and wheeze adventitious sounds have opposite behavior in the time-frequency domain. In order to better represent and resolve the discriminative characteristics of adventitious sounds, non-linear novel spectral feature extraction algorithms are proposed to be employed in four class classification problem. The proposed algorithm, which has achieved 49.86% accuracy on a very challenging and rich dataset, is a promising tool to be used as preprocessor in lung disease decision support systems.

Keywords

Adventitious pulmonary sounds • Respiratory sounds • Wheeze • Crackle • Respiration cycle

Introduction

Pulmonary diseases affect the comfort of the patients in their daily lives and some of the patients need to be tracked continuously for attacks and severe conditions. Low cost computerized pulmonary medical decision support systems may be employed to be used at home to monitor the status of the patient and this may reduce frequent hospital visits. However, in order to be used in clinical settings computerized systems must be validated in an objective way and should meet high accuracy requirements.

In literature, there are diverse approaches to explain 1 2]. Although the generation mechanisms are varied, the indicators of dysfunctions are extensively studied and the most well known indicators are wheeze and crackle sounds in the 3]. Wheezes are the oscillatory type of adventitious sounds whereas crackles are the transient type. These sounds represent opposite time-frequency (TF) characteristics and added onto normal (vesicular) breath sounds. The time and frequency content of normal, wheeze and crackle sounds are largely overlapped. Therefore, there is a need for an automatic system to provide fine TF resolution to resolve overlapped components of the pulmonary sounds. Moreover, an automatic system must deal with adventitious types of sounds without using prior information since some of them may be absent or consecutively present 1 2].

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In order to be used in medical decision support systems, detection and classification of pulmonary adventitious sounds with high accuracy is crucial. In literature, studies are 4 6], crackle/non-crackle classifi 7 9] and crackle-wheeze-normal classifi 10 12]. There are also 13 14] classification studies in literature. Wheeze and crackles may overlap or located consecutively in a breath cycle; moreover, it is reported that asthma and chronic obstructive pulmonary disease (COPD) may overlap on 15% of the obstructive lung disease popu- 15]. In the presence of these cases, to the best of our knowledge, there is no classification study which deals with wheeze and crackle sounds together in a breath cycle. In this paper, a novel time-frequency analysis based pulmonary sound classification system is proposed to classify pulmonary sound recordings into normal, crackle, wheeze and crackle-wheeze groups. Crackles are transient waveforms which typically last 20 ms with a scattered frequency con- 16]. On the other hand, wheezes are oscillatory 17]. Crackles are associated with pulmonary diseases such as COPD, chronic bronchitis, pneumonia, fibrosing alveolitis 16], whereas wheezes are associated with 18].

In literature, there are works which can be categorized 3]. Each approach has its own advantages. Segments are generally short duration (100 ms) time domain windows which include either wheeze or crackle sound types and their location is labelled by medical experts. On the other hand, events are long duration (10 s) time domain windows which include adventitious sounds but the exact location of the sound is not known or labelled. The latter is more difficult than the former since transient waveforms (crackles have 20 ms duration) may be located in any part of the long duration signal. Therefore, since crackles or wheezes may be present in the long duration window of the given lung sound, an automatic technique which has finer TF resolution is proposed to preprocess and classify crackle, wheeze, normal and crackle plus wheeze lung sound classes.

In section Materials and Methods", properties of the dataset and proposed novel time-frequency analysis based method is introduced. In section Results", experimental setup and results are represented. In section Conclusions", outcomes are discussed and conclusions are summarized.

Materials and Methods

Description of Dataset

The system is trained on a publicly available lung sound 19]. 4144 labelled respiratory cycles (2072 normal, 1209 crackle, 501 wheeze, 362 crackle plus wheeze) whose duration varies from 10 to 90s are used to form the dataset. Lung sounds are acquired using either microphones or digital stethoscopes from seven different locations on the chest wall. The dataset is very challenging and rich such that, it includes domestic and clinical recordings of children and adult subjects contaminated with various noise components such as coughing, talking, heart and intestinal sounds 19]. The test set is hidden and has different subjects, so that subject independent testing and training of the algorithm is guaranteed. The locations of the adventitious lung sounds are unknown and their labels are assigned by experts. Moreover, the dataset is collected from patients with different pulmonary disorders.

General Processing Steps of the Proposed System

1, the complete automatic preprocessing and classification system is represented step by step. As a preprocessing step, the given respiratory sound segment is band pass filtered to eliminate heart sounds and other noise components. Then the segment is separated into three channels to locate wheezes, crackles and background

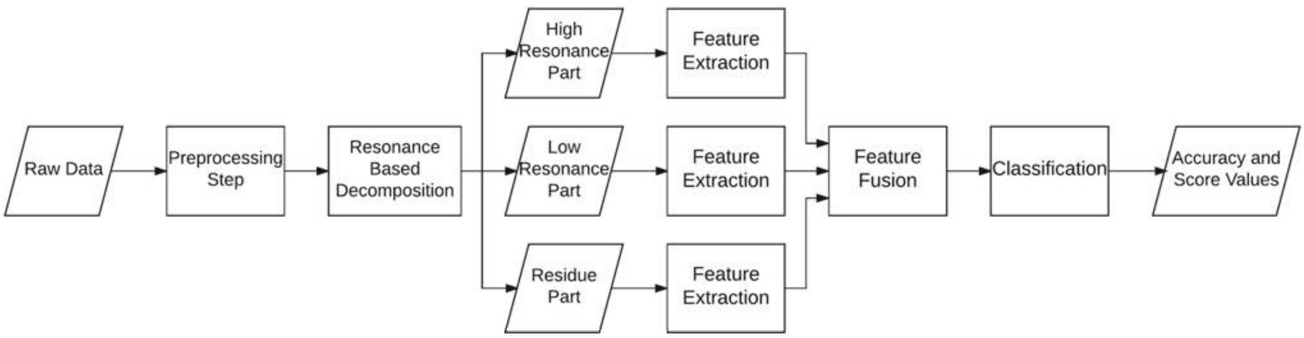

Fig. 1 Flowchart of the complete proposed preprocessing and classification system

(vesicular) sounds using resonance based decomposition 20]. Following that step, various time-frequency and time-scale analysis based features are extracted from each individual channel and a fusion of these features are fed into support vector machine classifier to train and test the proposed system. The details of each processing step of the system are presented below.

Preprocessing Step

At this step, the acquired raw lung sound data are down-sampled to 4000 Hz to set up a coherent feature set. Even on normal lung sound in the dataset which includes various noises such as intestinal and heart sounds and motion artefacts, 12th order Butterworth band pass filter with 120 and 1800 Hz cut-off frequencies is applied to minimize noise effects.

Proposed Time-Frequency and Time-Scale Analysis Based Method

Since the frequency ranges of lung sound types are highly overlapped and location of the adventitious sounds are 21], which is able to represent transient (crackle), oscillatory (wheeze) waveforms and noise components at separate channels, is applied to preprocessed lung sound segments. Adventitious lung sounds may contain both low and high frequency components, therefore instead of using linear frequency based decomposition, non-linear resonance based wavelet decomposition is proposed to decompose given lung sound into three channels. Oscillatory waveforms can be represented with high Q-factor wavelet, while transient waveforms can be better represented using low Q-factor wavelet bases. Once the given lung sound data are decomposed into high resonance (wheeze), low resonance (crackle) and residual (noise) parts, short time Fourier transform 22] is applied to each decomposed channel. In the beginning, after TF representation is formed, frequency content of each channel is computed by integrating the TF distribution over time. The motivation behind this step is to capture the discriminative frequency characteristics of lung sound types to better represent different classes because exact location of the adventitious sound is unknown and consequently, time information can not be used. Moreover, to better represent the discriminative characteristics of the dataset, statistical and spectral features derived from the wavelet coefficients are also employed to be used as additional features. Mean, skewness, kurtosis, standard deviation, minimum, maximum of the decomposed wavelet coefficients, linear energy and nonlinear Teager-Kaiser energy of the wavelet coefficients and entropy of wavelet coefficients are employed to increase the performance of the proposed system.

Feature Fusion and Classification

After the frequency features are extracted using STFT and 20], features are scaled to $[-1, +1]$ range to be normalized. In order to be employed in an online classification system, the dimension of the features is reduced using principal component analysis 23]. Various values of variance (90, 95 and 99%) are employed to measure the success of the proposed 24] with radial basis function kernel is employed by exploring the best fit $C(100)$ and $\gamma(0.001)$ parameters after various trials. Extracted STFT or STFT + Wavelet features are fed into the classifier algorithm. STFT is employed using window length of 256

Table 1 Various performance results of merely STFT and STFT + Wavelet based extracted features of proposed system employing different PCA variances

Method	Rate	PCA Variances		
		0.90	0.95	0.99
STFT	**Accuracy**	49.98	53.68	57.75
	Sensitivity	48.90	52.11	54.33
	Specificity	77.80	82.40	87.50
	Score	63.35	67.25	70.92
STFT + Wavelet	**Accuracy**	57.88	55.29	54.15
	Sensitivity	55.29	52.60	50.61
	Specificity	83.25	83.65	84.40
	Score	69.27	68.13	67.51

with 80% overlap on Hamming window. For the wavelet part, Q (Q-factor), r (over-sampling rate) and J (number of levels) values of 4, 5 and 45 are employed, respectively.

Results

1, the accuracy, specificity, sensitivity and score (exactly average of specificity and sensitivity) rates of merely STFT and STFT + Wavelet based proposed method is represented employing various PCA variances. As represented in the table, accuracy of the STFT + Wavelet based method is better than STFT even if only 90% of the PCA variance is employed. Moreover, when 90% of the PCA variance is employed the score of the STFT is 63.35%, while the score of the STFT + Wavelet based method is 69.27%. In order to be employed in real time systems, the dimension of the extracted features are reduced using PCA to decrease the computational load. STFT + Wavelet based algorithm represents decreasing performance while the recovered variance of the PCA is increased (except for the specificity 1. This is probably due to the reason that classifier is confused with the redundant information. These results are obtained on the training dataset, since the testing dataset is hidden, the results on the testing dataset could not be provided in detail.

The experimental results showed that proposed wavelet and Fourier based spectral features are not generalizable to the testing set. The reasons for this outcome may be that the kernel of the support vector machine could not be able to learn the bases, Fourier based spectral features could not be able to localize transient sounds (duration of crackles is 10 ms) in 10–90s recordings or normal respiratory sounds are confused with crackle segments due to various intestinal and other noise sources. In the testing experiments 39.97–49.86% accuracies are reached. It is seen that, the proposed STFT + Wavelet based features represent 1.20% better performance than proposed merely STFT based features on the testing dataset.

Conclusions

A robust and generalizable method is needed to classify respiratory sounds in the presence of various noises. Lower testing scores pointed out that either classifier or trained model show weaker generalizable representation. Redundancy in the extracted features may also decrease the classification performance. Detecting and classifying transient waveforms which last 20 ms in 10 s duration lung segment is very challenging in the presence of heart, intestinal sounds and stethoscope motion. Moreover, normal lung sound segments which include various noise sources may be confused with lung sound segments containing crackle sounds. More advanced spectral features and classifiers will be explored to increase the classification accuracy of the proposed system.

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Conflict of Interest The authors declare that they have no conflict of interest.

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