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(54) **SYSTEMS AND METHODS FOR DETECTING PULMONARY ABNORMALITIES USING LUNG SOUNDS**

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(57) **ABSTRACT**

Identification of pulmonary diseases involves accurate auscultation as well as elaborate and expensive pulmonary function tests. Also, there is a dependency on a reference signal from a flowmeter or need for labelled respiratory phases. The present disclosure provides extraction of frequency and time-frequency domain lung sound features such as spectral and spectrogram features respectively that enable classification of healthy and abnormal lung sounds without the dependencies of prior art. Furthermore extraction of wavelet and cepstral features improves accuracy of classification. The lung sound signals are pre-processed prior to feature extraction to eliminate heart sounds and reduce computational requirements while ensuring that information providing adequate discrimination between healthy and abnormal lung sounds is not lost.

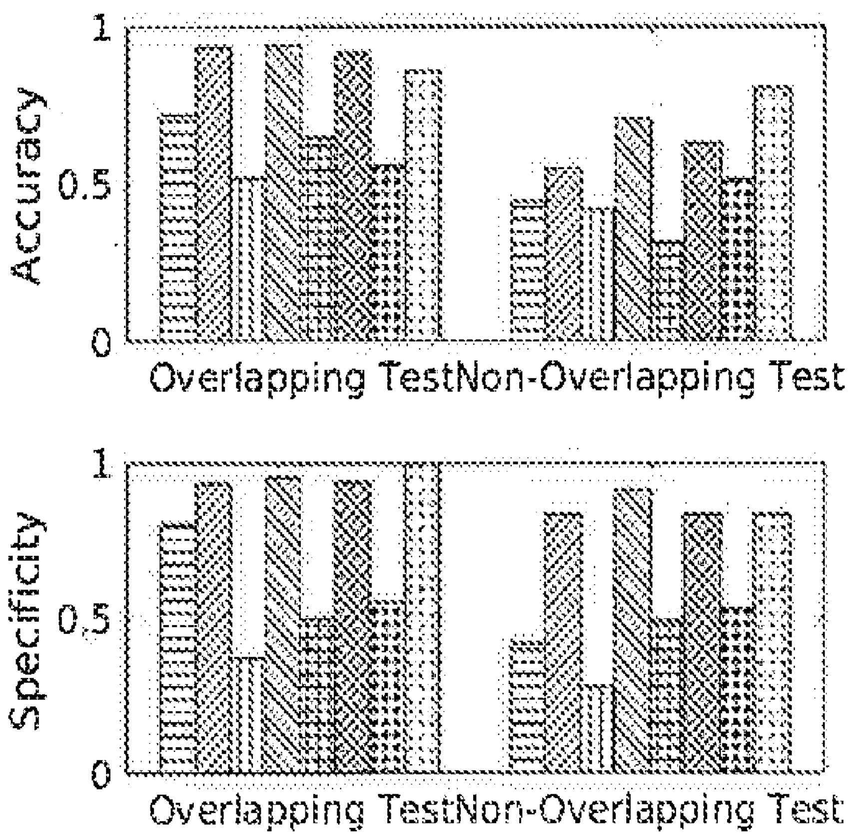


FIG.7C

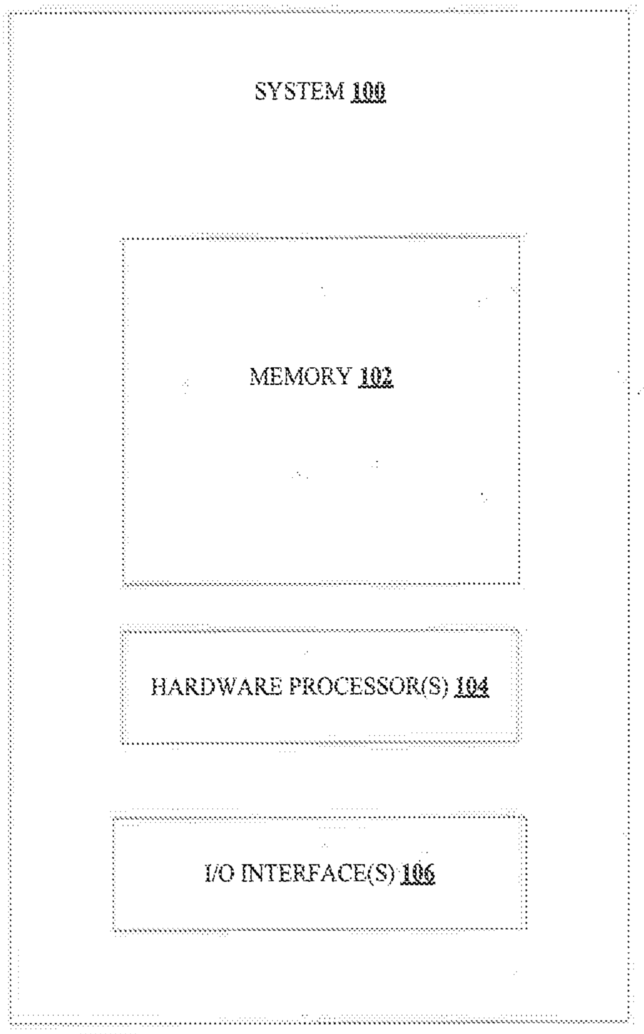

SYSTEM 100
MEMORY 102
HARDWARE PROCESSOR(S) 104
I/O INTERFACE(S) 106

FIG.1

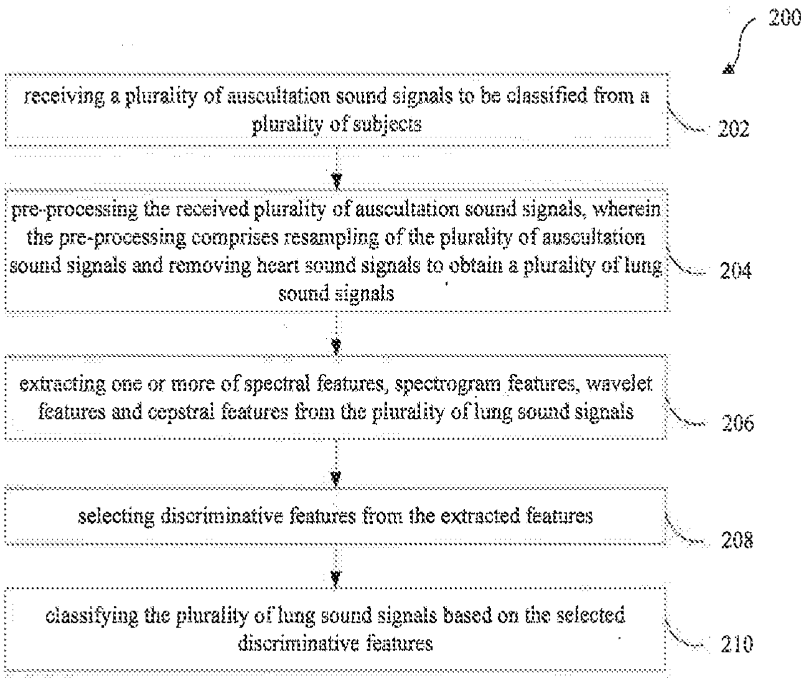

200
receiving a plurality of auscultation sound signals to be classified from a plurality of subjects
202
pre-processing the received plurality of auscultation sound signals, wherein the pre-processing comprises resampling of the plurality of auscultation sound signals and removing heart sound signals to obtain a plurality of lung sound signals
204
extracting one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals
206
selecting discriminative features from the extracted features
208
classifying the plurality of lung sound signals based on the selected discriminative features
210

FIG.2

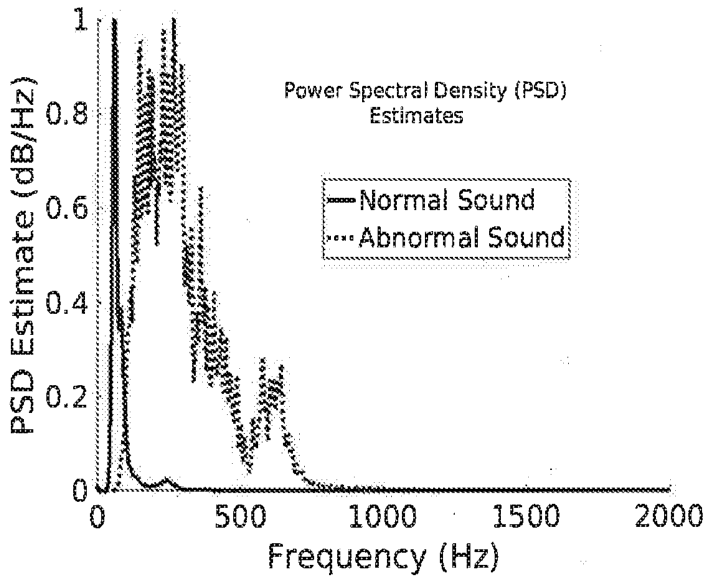

Power Spectral Density (PSD)
Estimates
Normal Sound
Abnormal Sound
PSD Estimate (dB/Hz)
1
0.8
0.6
0.4
0.2
0
0
500
1000
1500
2000
Frequency (Hz)

FIG.3

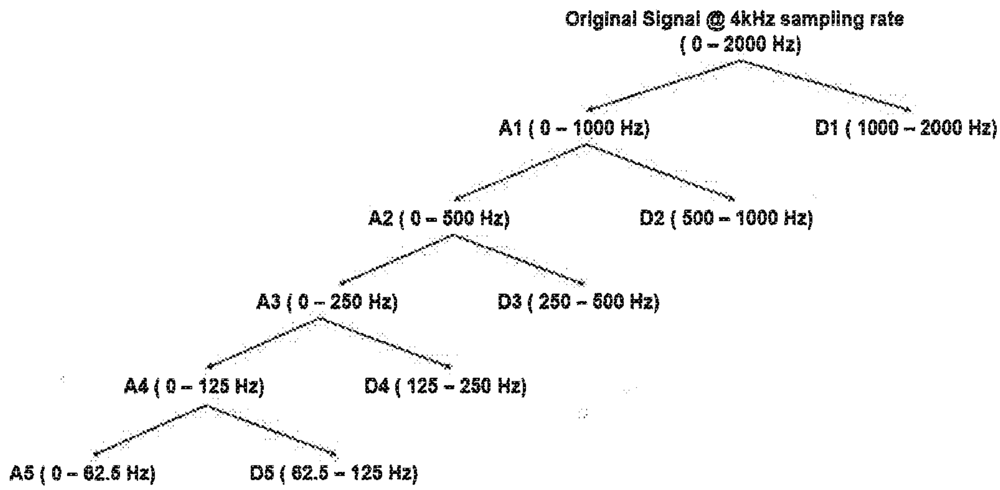

Original Signal @ 4kHz sampling rate
(0 ~ 2000 Hz)
A1 (0 ~ 1000 Hz)
D1 (1000 ~ 2000 Hz)
A2 (0 ~ 500 Hz)
D2 (500 ~ 1000 Hz)
A3 (0 ~ 250 Hz)
D3 (250 ~ 500 Hz)
A4 (0 ~ 125 Hz)
D4 (125 ~ 250 Hz)
A5 (0 ~ 62.5 Hz)
D5 (62.5 ~ 125 Hz)

FIG.4

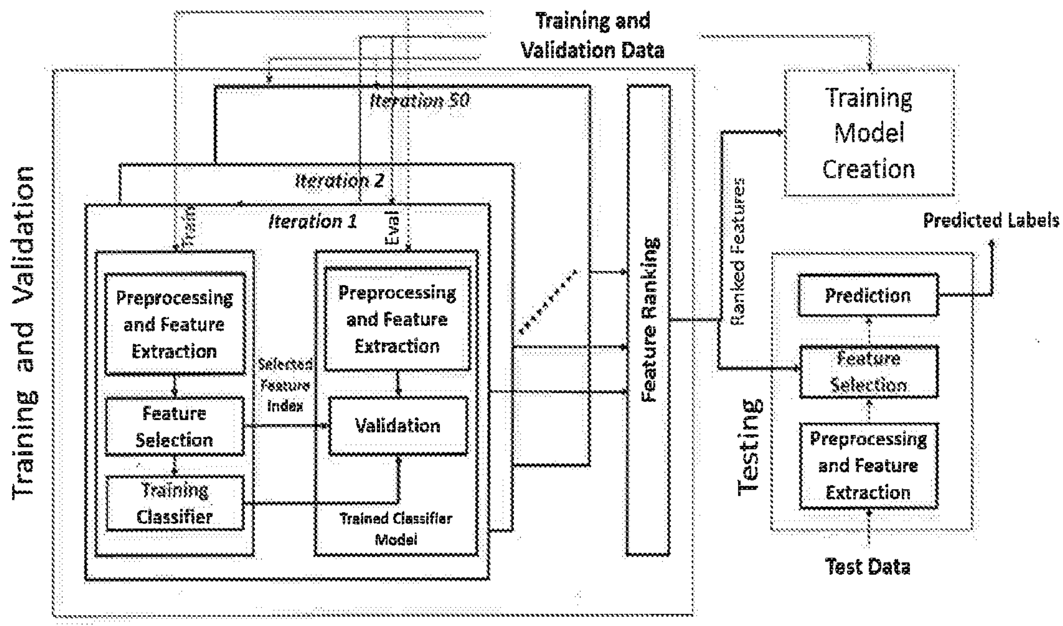

Training and Validation Data
Training and Validation
Iteration 50
Iteration 2
Iteration 1
Train
Eval
Preprocessing and Feature Extraction
Feature Selection
Training Classifier
Selected Feature Index
Preprocessing and Feature Extraction
Validation
Trained Classifier Model
Feature Ranking
Ranked Features
Training Model Creation
Predicted Labels
Testing
Prediction
Feature Selection
Preprocessing and Feature Extraction
Test Data

FIG.5

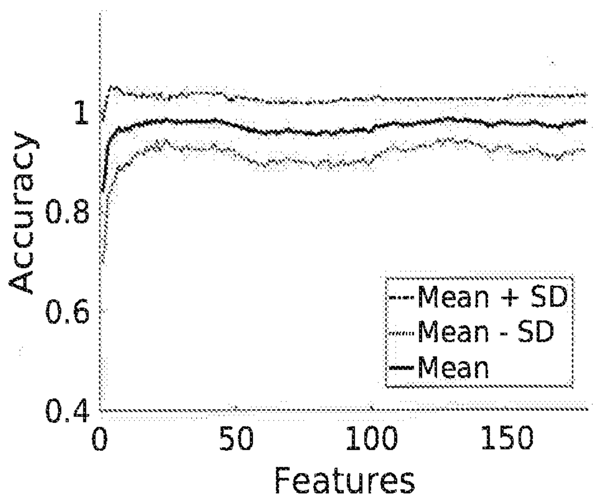


FIG.6A

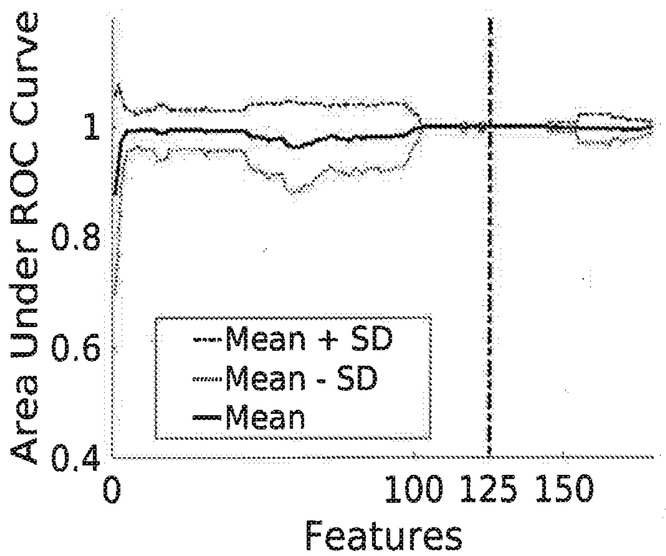

Area Under ROC Curve
1
0.8
0.6
0.4
0
100 125 150
Features
Mean + SD
Mean - SD
Mean

FIG.6B

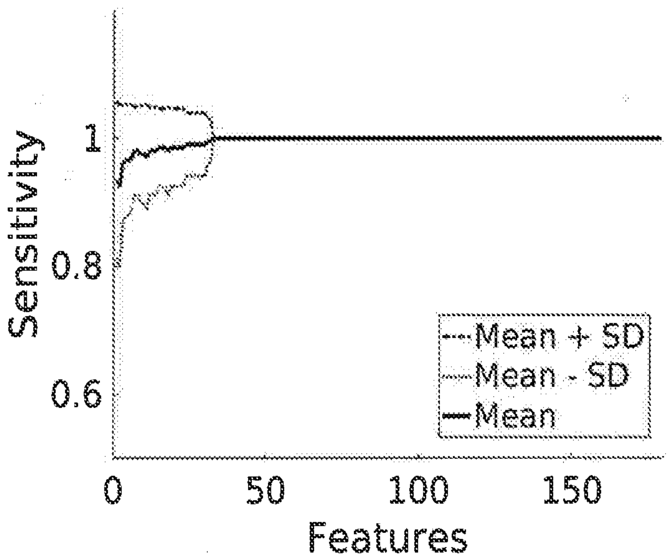


FIG.6C

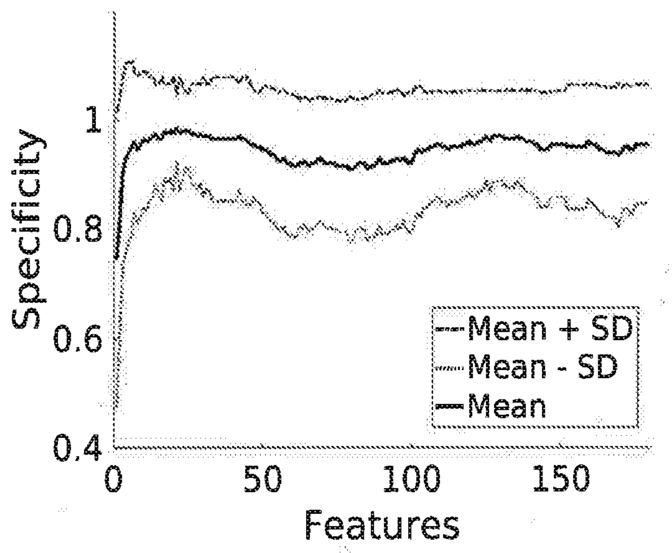

Specificity
1
0.8
0.6
0.4
0
50
100
150
Features
Mean + SD
Mean - SD
Mean

FIG.6D

FIG.7A

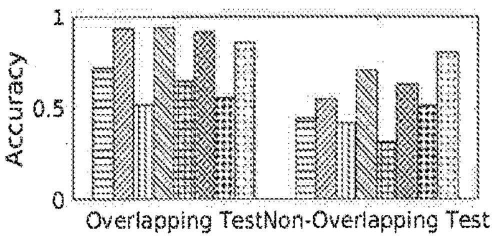
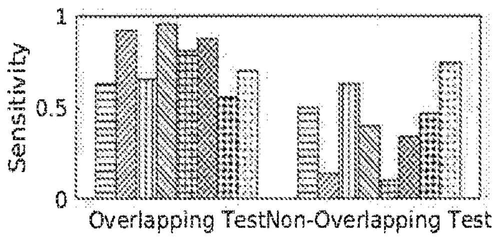


FIG.7B



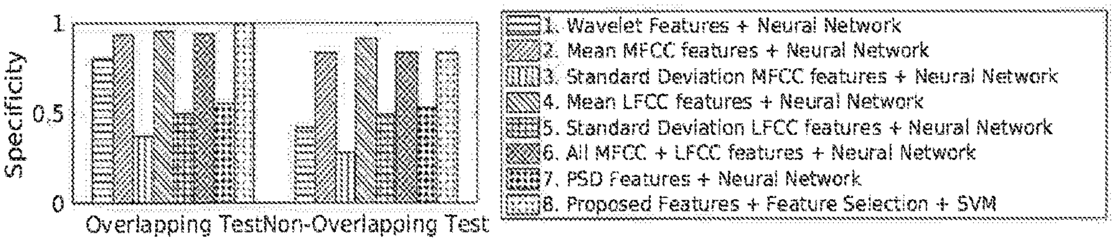


FIG.7C

SYSTEMS AND METHODS FOR DETECTING PULMONARY ABNORMALITIES USING LUNG SOUNDS

PRIORITY CLAIM

[0001] This U.S. patent application claims priority under 35 U.S.C. § 119 to: Indian Patent Application No. 201721023532, filed on 4 Jul. 2017. The entire contents of the aforementioned application are incorporated herein by reference.

TECHNICAL FIELD

[0002] The embodiments herein generally relate to detection and analyses of auscultation sound signals, and more particularly to systems and methods for detecting pulmonary abnormalities using lung sounds.

BACKGROUND

[0003] There has been a massive increase in the occurrence of pulmonary diseases worldwide, due to increasing pollution, effect of burning biomass, human habits like smoking and the like. Obstructive Airway Diseases (OAD) like Asthma or Chronic Obstructive Pulmonary Disease (COPD), characterized by narrowing of the airways has emerged as reasons for major concern. Identification of abnormal lung sounds is a first step in diagnoses of such diseases. Auscultation to screen the presence of abnormality is an entirely manual process and lung sounds being inherently aperiodic signals, an abnormality may not surface throughout a recording for a subject, making diagnosis difficult. Further, skewed doctor-to-patient ratio in developing countries often leads to failure in timely diagnosis. Traditional known methods for identification of abnormal lung sounds use a reference flowmeter signal along with lung sounds to label the respiratory phases or manually separate them out. Some conventional methods involve deep learning to identify features for lung sound analysis. However, such features are often not physically interpretable and hence not relevant to the medical fraternity for screening pulmonary abnormalities.

SUMMARY

[0004] Embodiments of the present disclosure present technological improvements as solutions to one or more of the above-mentioned technical problems recognized by the inventors in conventional systems.

[0005] In an aspect, there is provided a processor implemented method comprising: receiving a plurality of auscultation sound signals to be classified from a plurality of subjects; pre-processing the received plurality of auscultation sound signals, wherein the pre-processing comprises resampling of the plurality of auscultation sound signals and removing heart sound signals to obtain a plurality of lung sound signals; extracting one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals; selecting a plurality of discriminative features from the extracted features; and classifying the plurality of lung sound signals based on the selected discriminative features.

[0006] In another aspect, there is provided a system comprising: one or more data storage devices operatively coupled to the one or more processors and configured to store instructions configured for execution by the one or more processors to: receive a plurality of auscultation sound signals to be classified from a plurality of subjects; pre-process the received plurality of auscultation sound signals by resampling the plurality of auscultation sound signals and removing heart sound signals to obtain a plurality of lung sound signals; extract one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals; select a plurality of discriminative features from the extracted features; and classify the plurality of lung sound signals based on the selected discriminative features.

[0007] In yet another aspect, there is provided a computer program product comprising a non-transitory computer readable medium having a computer readable program embodied therein, wherein the computer readable program, when executed on a computing device, causes the computing device to: receive a plurality of auscultation sound signals to be classified from a plurality of subjects; preprocess the received plurality of auscultation sound signals by resampling the plurality of auscultation sound signals and removing heart sound signals to obtain a plurality of lung sound signals; extract one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals; select a plurality of discriminative features from the extracted features; and classify the plurality of lung sound signals based on the selected discriminative features.

[0008] In an embodiment of the present disclosure, the resampling comprises down-sampling the plurality of auscultation sound signals to a pre-defined frequency is based on a range of frequencies that provide optimum discrimination between healthy and abnormal lung sounds.

[0009] In an embodiment of the present disclosure, the step of removing heart sound signals is based on Empirical Mode Decomposition method.

[0010] In an embodiment of the present disclosure, the step of extracting features comprises dividing the plurality of lung sound signals into a plurality of overlapping windows.

[0011] In an embodiment of the present disclosure, the step of extracting spectral features comprises: computing periodograms for each of the plurality of overlapping windows; and averaging the periodograms to obtain a Power Spectral Density (PSD) estimate curve for the plurality of lung sound signals.

[0012] In an embodiment of the present disclosure, the extracted spectral features are areas under a normalized Power Spectral Density (PSD) estimate curve corresponding to a pre-defined number of frequency bands from 0-1.5 kHz (PS_1 to PS_{15}), ratio of the spectral power below 500 Hz (P_1) to that from 500 Hz to 1500 Hz (P_2), spectral centroid (S_{cent}), spectral flux (S_{flux}), spectral rolloff (S_{roll}) and spectral kurtosis (S_{kurt}), wherein the pre-defined number of frequency bands is selected such that optimum discrimination between healthy and abnormal lung sounds is achieved.

[0013] In an embodiment of the present disclosure, the extracted spectrogram features are median spectral powers (SP_1 to SP_{58}) across the plurality of overlapping windows, wherein the median spectral powers are computed for a pre-defined number of equally spaced frequencies between 0.15 kHz-1.5 kHz of the plurality of lung sound signals, the pre-defined number of equally spaced frequencies being based on the computational complexity and frequency resolution.

[0014] In an embodiment of the present disclosure, the step of extracting wavelet features comprises: selecting a best mother wavelet in each window of the plurality of overlapping windows based on maximum energy and minimum Shannon entropy criteria; decomposing the plurality of lung sound signals using the best mother wavelet into decomposition levels; and computing median of absolute values of approximation and detail coefficients for the decomposition levels.

[0015] In an embodiment of the present disclosure, the extracted wavelet features (W_1 to W_{21}) are (i) the median of absolute values of approximation and detail coefficients for the decomposition levels and (ii) ratios thereof across subbands of the plurality of overlapping windows.

[0016] In an embodiment of the present disclosure, the extracted cepstral features are mean ($mfccm_i$ and $lfccm_i$) and standard deviation ($mfccsd_i$ and $lfccsd_i$) of Mel Frequency Cepstral Coefficients (MFCC) and Linear Frequency Cepstral Coefficients (LFCC).

[0017] In an embodiment of the present disclosure, the step of selecting a plurality of discriminative features from the extracted features comprises: ranking the extracted features in decreasing order of importance; and selecting a plurality of discriminative features based on the optimal no. of features that result in a high performance value and a low standard deviation of a set of pre-defined performance metrics, wherein the set of predefined performance metrics comprise accuracy, sensitivity, specificity and area under the receiver operating characteristic curve.

[0018] It is to be understood that both the foregoing general description and the following detailed description are exemplary and explanatory only and are not restrictive of the embodiments of the present disclosure, as claimed.

BRIEF DESCRIPTION OF THE DRAWINGS

[0019] The embodiments herein will be better understood from the following detailed description with reference to the drawings, in which:

[0020] FIG. **1** illustrates an exemplary block diagram of a system for detecting pulmonary abnormalities using lung sounds, in accordance with an embodiment of the present disclosure;

[0021] FIG. **2** is an exemplary flow diagram illustrating a computer implemented method for detecting pulmonary abnormalities using lung sounds, in accordance with an embodiment of the present disclosure;

[0022] FIG. **3** illustrates Power Spectral Density (PSD) estimate curves for healthy and abnormal data pertaining to lung sound signals, in accordance with an embodiment of the present disclosure;

[0023] FIG. **4** illustrates wavelet decomposition showing regions of interest, in accordance with an embodiment of the present disclosure;

[0024] FIG. **5** illustrates a schematic representation of a supervised validation methodology, in accordance with an embodiment of the present disclosure;

[0025] FIG. **6**A through FIG. **6**D illustrate graphical representations of performance metrics viz., accuracy, Area under Receiver Operating Characteristics curve, sensitivity and specificity respectively during validation phase with sequential addition of features in accordance with an embodiment of the present disclosure; and

[0026] FIG. **7**A through FIG. **7**C illustrate graphical representations of performance metrics viz., accuracy, sensitivity and specificity respectively in accordance with an embodiment of the present disclosure when compared with methods known in the art.

[0027] It should be appreciated by those skilled in the art that any block diagram herein represent conceptual views of illustrative systems embodying the principles of the present subject matter. Similarly, it will be appreciated that any flow charts, flow diagrams, state transition diagrams, pseudo code, and the like represent various processes which may be substantially represented in computer readable medium and so executed by a computing device or processor, whether or not such computing device or processor is explicitly shown.

DETAILED DESCRIPTION

[0028] Exemplary embodiments are described with reference to the accompanying drawings. In the figures, the left-most digit(s) of a reference number identifies the figure in which the reference number first appears. Wherever convenient, the same reference numbers are used throughout the drawings to refer to the same or like parts. While examples and features of disclosed principles are described herein, modifications, adaptations, and other implementations are possible without departing from the spirit and scope of the disclosed embodiments. It is intended that the following detailed description be considered as exemplary only, with the true scope and spirit being indicated by the following claims.

[0029] Before setting forth the detailed explanation, it is noted that all of the discussion below, regardless of the particular implementation being described, is exemplary in nature, rather than limiting.

[0030] The present invention deals with lung sound analysis for predicting pulmonary abnormalities. In case of pulmonary defects, abnormal lung sounds such as wheezes, crackles, squeaks, stridors, etc. are present when breathing. Systems and methods of the present disclosure facilitate classifying whether a lung sound is abnormal or healthy (normal) based on certain characteristic features, particularly spectral and spectrogram features. No manual labeling of respiratory cycles or segmentation of lung sounds into respiratory cycles is necessary.

[0031] Referring now to the drawings, and more particularly to FIGS. **1** through **7**, where similar reference characters denote corresponding features consistently throughout the figures, there are shown preferred embodiments and these embodiments are described in the context of the following exemplary system and method.

[0032] FIG. **1** illustrates an exemplary block diagram of a system **100** for detecting pulmonary abnormalities using lung sounds, in accordance with an embodiment of the present disclosure. In an embodiment, the system **100** includes one or more processors **104**, communication interface device(s) or input/output (I/O) interface(s) **106**, and one or more data storage devices or memory **102** operatively coupled to the one or more processors **104**. The one or more processors **104** that are hardware processors can be implemented as one or more microprocessors, microcomputers, microcontrollers, digital signal processors, central processing units, state machines, graphics controllers, logic circuitries, and/or any devices that manipulate signals based on operational instructions. Among other capabilities, the processor(s) are configured to fetch and execute computer-readable instructions stored in the memory. In an embodiment, the system **100** can be implemented in a variety of computing systems, such as laptop computers, notebooks, hand-held devices, workstations, mainframe computers, servers, a network cloud and the like.

[0033] The I/O interface device(s) **106** can include a variety of software and hardware interfaces, for example, a web interface, a graphical user interface, and the like and can facilitate multiple communications within a wide variety of networks N/W and protocol types, including wired networks, for example, LAN, cable, etc., and wireless networks, such as WLAN, cellular, or satellite. In an embodiment, the I/O interface device(s) can include one or more ports for connecting a number of devices to one another or to another server.

[0034] The memory **102** may include any computer-readable medium known in the art including, for example, volatile memory, such as static random access memory (SRAM) and dynamic random access memory (DRAM), and/or non-volatile memory, such as read only memory (ROM), erasable programmable ROM, flash memories, hard disks, optical disks, and magnetic tapes. In an embodiment, one or more modules (not shown) of the system **100** can be stored in the memory **102**.

[0035] FIG. **2** is an exemplary flow diagram illustrating a computer implemented method **200** for detecting pulmonary abnormalities using lung sounds, in accordance with an embodiment of the present disclosure. In an embodiment, the system **100** comprises one or more data storage devices or memory **102** operatively coupled to the one or more processors **104** and is configured to store instructions configured for execution of steps of the method **200** by the one or more processors **104**.

[0036] The steps of the method **200** will now be explained in detail with reference to the components of the system **100** of FIG. **1**. In accordance with the present disclosure, the one or more processors **104** are configured to receive, at step **202**, a plurality of auscultation sound signals to be classified from a plurality of subjects. In an embodiment, acquisition of auscultation sound signals involves using a digital stethoscope. Lung sounds are inherently contaminated with heart sounds. Also, different sampling rates exist when different sources (types of stethoscopes) are used. In an embodiment, the one or more processors **104** are configured to pre-process the received plurality of auscultation sound signals at step **204**. The step of pre-processing comprises resampling of the plurality of auscultation sound signals and removing undesired heart sound signals to obtain a plurality of lung sound signals. Heart sound signals may be removed by Empirical Mode Decomposition method. The resampling comprises down-sampling the plurality of auscultation sound signals to a pre-defined frequency based on a range of frequencies that provide optimum discrimination between healthy (normal) and abnormal lung sounds. In an embodiment, the auscultation sound signals are downsampled to 4 kHz (Nyquist theorem) as necessary information to classify lung sound signals into healthy and abnormal classes lies within 2 kHz.

[0037] In an embodiment, the one or more processors **104** are configured to extract, at step **206**, one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals. In accordance with the present disclosure, adding two or more feature types enhances accuracy of classification of the lung sound signals as explained herein after. The step of extracting features firstly comprises dividing the plurality of lung sound signals (session) into a plurality of overlapping windows or segments.

[0038] In accordance with the present disclosure, spectral characteristics of lung sound signals may be used to discriminate healthy and abnormal classes. Firstly, periodograms are computed for each of the plurality of overlapping windows. In an embodiment, Welch method may be used for computing the periodograms. The periodograms are then averaged to obtain a Power Spectral Density (PSD) estimate curve for the plurality of lung sound signals. FIG. **3** illustrates Power Spectral Density (PSD) estimate curves for healthy (normal) and abnormal data pertaining to lung sound signals, in accordance with an embodiment of the present disclosure. It may be noted that area under a normalized PSD curve is significantly higher for an abnormal sound compared to a healthy sound. However, the exact spread of the area varies with the degree and nature of the abnormality. In an embodiment, a normalized Welch PSD curve is obtained using windows of 1024 samples and 50% overlap at 15 frequency bands with overlapping windows of 1 sec. Accordingly, in accordance with the present disclosure, the spectral features that may be extracted to aid classification of the lung sound signals are areas under a normalized Power Spectral Density (PSD) estimate curve corresponding to a pre-defined number of frequency bands from 0-1.5 kHz (PS_1 to PS_{15}), ratio of the spectral power below 500 Hz (P_1) to that from 500 Hz to 1500 Hz (P_2), spectral centroid (S_{cent}), spectral flux (S_{flux}), spectral rolloff (S_{roll}) and spectral kurtosis (S_{kurt}), wherein the pre-defined number of frequency bands is selected such that optimum discrimination between normal and abnormal lung sounds is achieved.

[0039] Lung sound being nonstationary in nature, a spectrogram analysis reveals the change of frequency with time. For each session spectrograms with windows of length 512 and 480 point overlap were created using 512 point FFT. It is known that spectral power for lung sounds in the range of 0.15 kHz-1.5 kHz is significantly higher in abnormal lung sounds compared to healthy lung sounds. However, the exact spread of the frequency is strongly correlated with the nature of the abnormality. From the spectrogram, 58 equally spaced frequencies between 0.15 kHz-1.5 kHz are selected ensuring a trade-off between computational complexity and higher frequency resolution, after checking the performance during validation. For each such frequency, the median spectral power across all time windows are used, thereby getting spectral powers SP_1 to SP_{58}. The spectral power at each frequency is normalized with respect to the total spectral power at all frequencies. Thus, in accordance with the present disclosure, spectrogram features that may be extracted to aid classification of the lung sound signals are median spectral powers (SP_1 to SP_{58}) across the plurality of overlapping windows, wherein the median spectral powers are computed for a pre-defined number of equally spaced frequencies between 0.15 kHz-1.5 kHz of the plurality of lung sound signals, the pre-defined number of equally spaced frequencies being based on the computational complexity and frequency resolution.

[0040] Discrete Wavelet Transform (DWT) represents a signal in multiple frequency bands by decomposing it into approximation and detail information. The decomposition level is determined by the frequency band of interest, wherein decomposing of the plurality of lung sound signals is done using a best mother wavelet selected in each window based on maximum energy and minimum Shannon entropy criteria For a signal sampled at 4 kHz (i.e. maximum information content till 2 kHz), the approximation (A_i) and detail (D_i) coefficients at the i^{th} level, for all decomposition levels is illustrated in FIG. **4**. Based on the region of interest on the frequency domain (0-2000 Hz), a median of the absolute values of the D1, D2, D3, D4, D5 and A5 coefficients as illustrated in FIG. **4** and their ratios over all windows are used as wavelet features (W_1 to W_{21}). In accordance with the present disclosure, the values of the coefficients are normalized with respect to all sub-bands of all the windows and the ratios of the features between all sub-bands are taken.

[0041] In accordance with the present disclosure, the cepstral features that may be extracted to aid classification of the lung sound signals are mean ($mfccm_i$ and $lfccm_i$) and standard deviation ($mfccsd_i$ and $lfccsd_i$) of Mel Frequency Cepstral Coefficients (MFCC) and Linear Frequency Cepstral Coefficients (LFCC). To extract these features, in an embodiment, the signals are divided into windows of 50 ms and 50% overlap and the signals are analyzed between 0-2000 Hz.

[0042] Table I herein below depicts all features and their respective indices used as reference in the present disclosure.

TABLE I

Description of features used

Feature Index	Description
1 to 20	Spectral features: PS_1 to PS_{15}, P_1/P_2, S_{cent}, S_{flux}, S_{roll}, S_{kurt}
21 to 78	Spectrogram features: SP_1 to SP_{58}
79 to 99	Wavelet features: W_1 to W_{21}
100 to 179	Cepstral Features: $mfccm_1$ to $mfccm_{20}$, $mfccsd_1$ to $mfccsd_{20}$, $lfccm_1$ to $lfccm_{20}$, $lfccsd_1$ to $lfccsd_{20}$

[0043] In an embodiment, the one or more processors (**104**) are configured to select, at step **208**, a plurality of discriminative features from the extracted features of step **206**. The step of selecting discriminative features is critical to avoid irrelevant or redundant features. In an embodiment, the step of selecting a plurality of discriminative features from the extracted features comprises ranking the extracted features in decreasing order of importance; and selecting a plurality of discriminative features based on the optimal no. of features that result in a high performance value and a low standard deviation of a set of pre-defined performance metrics. In an embodiment, Maximal Information Coefficient (MIC) based feature selection algorithm may be used. In an embodiment, the set of pre-defined performance metrics comprise accuracy, sensitivity, specificity and area under the receiver operating characteristic curve.

[0044] In an embodiment, the one or more processors (**104**) are configured to classify, at step **210**, the plurality of lung sound signals based on the selected discriminative features. A linear Support Vector Machine (SUM) classifier may be used to classify the lung sounds based on the selected discriminative features. The tolerance of termination criterion may be set to 0.001, though experimentations over a validation set revealed no major change in performance with slight variation in the tolerance.

[0045] Results and Observations

Dataset:

[0046] A lung sound dataset comprising 52 lung sound signals equally distributed among healthy and abnormal classes was created from different data sources. The abnormal lung sound signals were obtained from a) RALE Lung Sound Repository and b) Steven Lehrer Lung Sound Repository. Both these data sources have lung sounds labelled by physicians to be healthy or having some form of abnormality. The abnormalities include different forms of wheezes and crackles along with squawks, stridors, grunting, squeaks and pleural rub. These were collected from subjects of various age groups and from different chest locations. Some of the healthy sounds were collected from healthy individuals working in the lab using either an in-house digital stethoscope that records audio data at 8 kHz through an android application on a Nexus 5 smartphone or the 3M Littmann Electronic Stethoscope Model 32005 at 4 kHz. Some other normal sounds were acquired from the RALE Lung Sound Repository. The sampling rates of the RALE data and Steven Lehrer data are respectively 11.025 kHz and 44.1 kHz. The lab data were collected from either tracheal position or posterior chest walls.

Performance Metrics:

[0047] Standard classification metrics accuracy, sensitivity and

specificity were used to evaluate the performance of the methods of the present disclosure along with area (AUC) under the Receiver Operating Characteristics (ROC) curve, that shows the variation of the true positive rate with the false positive rate.

[0048] Results:

[0049] FIG. **5** illustrates a schematic representation of a supervised validation methodology, in accordance with an embodiment of the present disclosure. The dataset was separated into two subsets: a) for training and validation (validation phase—VP) and b) for testing (testing phase—TP). In VP, 70% of the data was randomly selected for training and the remaining 30% was used for evaluation. The training and evaluation subsets contain data with equally distributed samples from both healthy and abnormal classes. To mitigate the problem of relatively small sample size, the validation process was repeated for 50 times as shown in FIG. **5**. For each such iteration, MIC was used to select the best features from the training subset only. Thereby the selected features and the training model were used to evaluate the performance of the evaluation set. For each iteration, features were sequentially added in order of decreasing importance and the performance was noted.

[0050] FIG. **6**A through FIG. **6**D illustrate graphical representations of performance metrics viz., accuracy, Area under Receiver Operating Characteristics curve, sensitivity and specificity respectively during validation phase with sequential addition of features in accordance with an embodiment of the present disclosure. The Mean±SD values of the performance metrics over all 50 iterations are shown in FIG. **6**A through FIG. **6**D with the sequential addition of features. A final rank list showing the best 16 features obtained from their median ranks over the 50 iterations is provided in Table II, along with the Mean±SD values for the respective features for each class.

TABLE II

Best 16 features selected after validation phase

		Rank							
		1	2	3	4	5	6	7	8
	Index	109	116	154	100	105	155	140	159
Mean ± SD	Healthy	6.5 ± 2.9	−1.67 ± 0.78	1.55 ± 0.59	52.42 ± 15.89	4.72 ± 3.61	1.83 ± 0.85	49.36 ± 15.71	0.37 ± 0.25
	Abnormal	−0.08 ± 3.47	0.14 ± 0.56	−0.4 ± 1.2	25.89 ± 30.24	−1.59 ± 5.44	−0.08 ± 0.95	24.67 ± 29.62	−0.02 ± 0.16
		Rank							
		9	10	11	12	13	14	15	16
	Index	19	143	54	63	64	12	62	65
Mean ± SD	Healthy	133.48 ± 52.65	5.78 ± 5.04	(37 ± 15) × 10^{-5}	(22 ± 9) × 10^{-5}	(21 ± 9) × 10^{-5}	(19 ± 13) × 10^{-4}	(23 ± 9) × 10^{-5}	(20 ± 9) × 10^{-5}
	Abnormal	248.52 ± 141.58	−0.4 ± 3.41	(15 ± 17) × 10^{-4}	(11 ± 16) × 10^{-4}	(11 ± 15) × 10^{-4}	0.65 ± 2.82	(12 ± 20) × 10^{-4}	(9 ± 13) × 10^{-4}

[0051] It may also be noted that the features proposed in accordance with the present disclosure provide clear evidence of discrimination between normal and abnormal lung sounds. In the final ordered feature list, 47 of the first 100 features are either the spectral or spectrogram features in accordance with the present disclosure which may be justified by the remarkable difference between the PSD estimates and spectrograms for the two classes of sound data (refer FIG. **3**). To freeze the number of features, a high performance value with a low standard deviation of the metrics is chosen. As evident in FIG. **6**B though performance value is high before the first 100 features, the standard deviation decreases and remains consistently low in the range of 100-150 features. As a tradeoff between the performance and computational requirements (which increases with the number of features) the first 125 features from VP are selected.

[0052] FIG. **7**A through FIG. **7**C illustrate graphical representations of performance metrics viz., accuracy, sensitivity and specificity respectively in accordance with an embodiment of the present disclosure when compared with methods known in the art. Results are reported for two test cases: (a) overlapping Test: VP and TP contain data from separate subjects but from overlapping data sources and (b) Non-overlapping Test: VP and TP contain data from separate subjects as well as non-overlapping data sources. The results in FIG. **7**A through FIG. **7**C show that though the prior arts produce decent performance for overlapping test, the performance drastically degrades for the non-overlapping Test. Particularly, the sensitivity, and hence accuracy, for methods 2, 4 and 6 of FIG. **7**A through FIG. **7**C (prior art), drops for the non-overlapping test. However, the method of the present disclosure maintains a consistently high performance (accuracy of 85% and 80% for overlapping and non-overlapping test respectively).

[0053] Thus in accordance with the present disclosure, systems and methods described herein above provide an automated lung sound analysis platform to identify abnormal lung sounds without the use of any reference signal from a flowmeter or labelling of the respiratory phases. Particularly spectral and spectrogram features have been identified which when used along with wavelet and cepstral features enhance accuracy of the classification of lung sound signals. An automated feature selection on a validation set followed by evaluation on a separate test data source ensures elimination of overfitting but still yields a high performance. Accuracy of classification remains high with a balance in the sensitivity and specificity.

[0054] The written description describes the subject matter herein to enable any person skilled in the art to make and use the embodiments of the present disclosure. The scope of the subject matter embodiments defined here may include other modifications that occur to those skilled in the art. Such other modifications are intended to be within the scope if they have similar elements that do not differ from the literal language of the claims or if they include equivalent elements with insubstantial differences from the literal language.

[0055] The scope of the subject matter embodiments defined here may include other modifications that occur to those skilled in the art. Such other modifications are intended to be within the scope if they have similar elements that do not differ from the literal language of the claims or if they include equivalent elements with insubstantial differences from the literal language.

[0056] It is, however to be understood that the scope of the protection is extended to such a program and in addition to a computer-readable means having a message therein; such computer-readable storage means contain program-code means for implementation of one or more steps of the method, when the program runs on a server or mobile device or any suitable programmable device. The hardware device can be any kind of device which can be programmed including e.g. any kind of computer like a server or a personal computer, or the like, or any combination thereof. The device may also include means which could be e.g. hardware means like e.g. an application-specific integrated circuit (ASIC), a field-programmable gate array (FPGA), or a combination of hardware and software means, e.g. an ASIC and an FPGA, or at least one microprocessor and at least one memory with software modules located therein. Thus, the means can include both hardware means and software means. The method embodiments described herein could be implemented in hardware and software. The device may also include software means. Alternatively, the embodiments of the present disclosure may be implemented on different hardware devices, e.g. using a plurality of CPUs.

[0057] The embodiments herein can comprise hardware and software elements. The embodiments that are implemented in software include but are not limited to, firmware, resident software, microcode, etc. The functions performed by various modules comprising the system of the present disclosure and described herein may be implemented in other modules or combinations of other modules. For the purposes of this description, a computer-usable or computer readable medium can be any apparatus that can comprise, store, communicate, propagate, or transport the program for use by or in connection with the instruction execution system, apparatus, or device. The various modules described herein may be implemented as software and/or hardware modules and may be stored in any type of non-transitory computer readable medium or other storage device. Some non-limiting examples of non-transitory computer-readable media include CDs, DVDs, BLU-RAY, flash memory, and hard disk drives.

[0058] Further, although process steps, method steps, techniques or the like may be described in a sequential order, such processes, methods and techniques may be configured to work in alternate orders. In other words, any sequence or order of steps that may be described does not necessarily indicate a requirement that the steps be performed in that order. The steps of processes described herein may be performed in any order practical. Further, some steps may be performed simultaneously.

[0059] The illustrated steps are set out to explain the exemplary embodiments shown, and it should be anticipated that ongoing technological development will change the manner in which particular functions are performed. These examples are presented herein for purposes of illustration, and not limitation. Further, the boundaries of the functional building blocks have been arbitrarily defined herein for the convenience of the description. Alternative boundaries can be defined so long as the specified functions and relationships thereof are appropriately performed. Alternatives (including equivalents, extensions, variations, deviations, etc., of those described herein) will be apparent to persons skilled in the relevant art(s) based on the teachings contained herein. Such alternatives fall within the scope and spirit of the disclosed embodiments. Also, the words "comprising," "having," "containing," and "including," and other similar forms are intended to be equivalent in meaning and be open ended in that an item or items following any one of these words is not meant to be an exhaustive listing of such item or items, or meant to be limited to only the listed item or items. It must also be noted that as used herein and in the appended claims, the singular forms "a," "an," and "the" include plural references unless the context clearly dictates otherwise.

[0060] It is intended that the disclosure and examples be considered as exemplary only, with a true scope and spirit of disclosed embodiments being indicated by the following claims.

What is claimed is:

1. A processor implemented method (**200**) comprising:

receiving a plurality of auscultation sound signals to be classified from a plurality of subjects (**202**);

pre-processing the received plurality of auscultation sound signals, wherein the pre-processing comprises resampling of the plurality of auscultation sound signals and removing heart sound signals to obtain a plurality of lung sound signals (**204**);

extracting one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals (**206**);

selecting a plurality of discriminative features from the extracted features (**208**); and

classifying the plurality of lung sound signals based on the selected discriminative features (**210**).

2. The processor implemented method of claim **1**, wherein the resampling comprises down-sampling the plurality of auscultation sound signals to a pre-defined frequency based on a range of frequencies that provide optimum discrimination between healthy and abnormal lung sounds.

3. The processor implemented method of claim **1**, wherein the step of removing heart sound signals is based on Empirical Mode Decomposition method.

4. The processor implemented method of claim **1**, wherein the step of extracting comprises dividing the plurality of lung sound signals into a plurality of overlapping windows.

5. The processor implemented method of claim **1**, wherein the step of extracting spectral features comprises:

computing periodograms for each of the plurality of overlapping windows; and

averaging the periodograms to obtain a Power Spectral Density (PSD) estimate curve for the plurality of lung sound signals.

6. The processor implemented method of claim **5**, wherein the extracted spectral features are areas under a normalized Power Spectral Density (PSD) estimate curve corresponding to a pre-defined number of frequency bands from 0-1.5 kHz (PS_1 to PS_{15}), ratio of the spectral power below 500 Hz (P_1) to that from 500 Hz to 1500 Hz (P_2), spectral centroid (S_{cent}), spectral flux (S_{flux}), spectral rolloff (S_{roll}) and spectral kurtosis (S_{kurt}), wherein the pre-defined number of frequency bands is selected such that optimum discrimination between healthy and abnormal lung sounds is achieved.

7. The processor implemented method of claim **4**, wherein the extracted spectrogram features are median spectral powers (SP_1 to SP_{58}) across the plurality of overlapping windows, wherein the median spectral powers are computed for a predefined number of equally spaced frequencies between 0.15 kHz-1.5 kHz of the plurality of lung sound signals, the pre-defined number of equally spaced frequencies being based on the computational complexity and frequency resolution.

8. The processor implemented method of claim **4**, wherein the step of extracting wavelet features comprises:

selecting a best mother wavelet in each window of the plurality of overlapping windows based on maximum energy and minimum Shannon entropy criteria;

decomposing the plurality of lung sound signals using the best mother wavelet into decomposition levels; and

computing median of absolute values of approximation and detail coefficients for the decomposition levels.

9. The processor implemented method of claim **8**, wherein the extracted wavelet features (W_1 to W_{21}) are (i) the median of absolute values of approximation and detail coefficients for the decomposition levels and (ii) ratios thereof across sub-bands of the plurality of overlapping windows.

10. The processor implemented method of claim **4**, wherein the extracted cepstral features are mean ($mfccm_i$ and $lfccm_i$) and standard deviation ($mfccsd_i$ and $lfccsd_i$) of

Mel Frequency Cepstral Coefficients (MFCC) and Linear Frequency Cepstral Coefficients (LFCC).

11. The processor implemented method of claim **1**, wherein the step of selecting a plurality of discriminative features from the extracted features comprises:

ranking the extracted features in decreasing order of importance; and

selecting a plurality of discriminative features based on the optimal no. of features that result in a high performance value and a low standard deviation of a set of pre-defined performance metrics.

12. The processor implemented method of claim **11**, wherein the set of pre-defined performance metrics comprise accuracy, sensitivity, specificity and area under the receiver operating characteristic curve.

13. A system (**100**) comprising:

one or more data storage devices (**102**) operatively coupled to one or more hardware processors (**104**) and configured to store instructions configured for execution by the one or more hardware processors to:

receive a plurality of auscultation sound signals to be classified from a plurality of subjects;

pre-process the received plurality of auscultation sound signals by resampling the plurality of auscultation sound signals and removing heart sound signals to obtain a plurality of lung sound signals, wherein the resampling is performed by down-sampling the plurality of auscultation sound signals to a pre-defined frequency based on a range of frequencies that provide optimum discrimination between healthy and abnormal lung sounds;

extract one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals;

select a plurality of features from the extracted features; and

classify the plurality of lung sound signals based on the selected discriminative features.

14. The system of claim **13**, wherein the extracted spectral features are areas under a normalized Power Spectral Density (PSD) estimate curve corresponding to a pre-defined number of frequency bands from 0-1.5 kHz (PS_1 to PS_{15}), ratio of the spectral power below 500 Hz (P_1) to that from 500 Hz to 1500 Hz (P_2), spectral centroid (S_{cent}), spectral flux (S_{flux}), spectral rolloff (S_{roll}) and spectral kurtosis (S_{kurt}), wherein the pre-defined number of frequency bands is selected such that optimum discrimination between healthy and abnormal lung sounds is achieved.

15. The system of claim **13**, wherein the extracted spectrogram features are median spectral powers (SP_1 to SP_{58}) across a plurality of overlapping windows obtained by dividing the plurality of lung sound signals, wherein the median spectral powers are computed for pre-defined number of equally spaced frequencies between 0.15 kHz-1.5 kHz of the plurality of lung sound signals, the pre-defined number of equally spaced frequencies being based on the computational complexity and frequency resolution.

16. The system of claim **13**, wherein the extracted wavelet features (W_1 to W_{21}) are (i) median of absolute values of approximation and detail coefficients for decomposition levels obtained from the plurality of lung sound signals using a best mother wavelet and (ii) ratios thereof across sub-bands of a plurality of overlapping windows obtained by dividing the plurality of lung sound signals.

17. The system of claim **13**, wherein the extracted cepstral features are mean ($mfccm_i$ and $lfcccm_i$) and standard deviation ($mfccsd_i$ and $lfccsd_i$) of Mel Frequency Cepstral Coefficients (MFCC) and Linear Frequency Cepstral Coefficients (LFCC).

18. The system of claim **13**, wherein the one or more hardware processors are further configured to select a plurality of discriminative features from the extracted features by:

ranking the extracted features in decreasing order of importance; and

selecting a plurality of discriminative features based on the optimal no. of features that result in a high performance value and a low standard deviation of a set of pre-defined performance metrics.

19. The system of claim **18**, wherein the set of pre-defined performance metrics comprise accuracy, sensitivity, specificity and area under the receiver operating characteristic curve.

20. A computer program product comprising a non-transitory computer readable medium having a computer readable program embodied therein, wherein the computer readable program, when executed on a computing device, causes the computing device to:

receive a plurality of auscultation sound signals to be classified from a plurality of subjects;

pre-process the received plurality of auscultation sound signals by resampling the plurality of auscultation sound signals and removing heart sound signals to obtain a plurality of lung sound signals;

extract one or more of spectral features, spectrogram features, wavelet features and cepstral features from the plurality of lung sound signals;

select a plurality of features from the extracted features; and

classify the plurality of lung sound signals based on the selected discriminative features.

* * * * *

专利名称(译)	使用肺部声音检测肺部异常的系统和方法		
公开(公告)号	[US20190008475A1](US20190008475A1)	公开(公告)日	2019-01-10
申请号	US15/912234	申请日	2018-03-05
申请(专利权)人(译)	塔塔咨询服务有限公司		
当前申请(专利权)人(译)	塔塔咨询服务有限公司		
[标]发明人	DATTA SHREYASI DUTTA CHOUDHURY ANIRBAN DESHPANDE PARIJAT BHATTACHARYA SAKYAJIT PAL ARPAN		
发明人	DATTA, SHREYASI DUTTA CHOUDHURY, ANIRBAN DESHPANDE, PARIJAT BHATTACHARYA, SAKYAJIT PAL, ARPAN		
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摘要(译)

肺部疾病的鉴定涉及准确的听诊以及精细和昂贵的肺功能测试。此外，依赖于来自流量计的参考信号或需要标记的呼吸阶段。本公开提供频率和时频域肺声音特征的提取，例如光谱和频谱图特征，其分别能够分类健康和异常肺部声音，而没有现有技术的依赖性。此外，小波和倒谱特征的提取提高了分类的准确性。在特征提取之前对肺声音信号进行预处理以消除心音并降低计算要求，同时确保不会丢失在健康和异常肺部声音之间提供充分区分的信息。

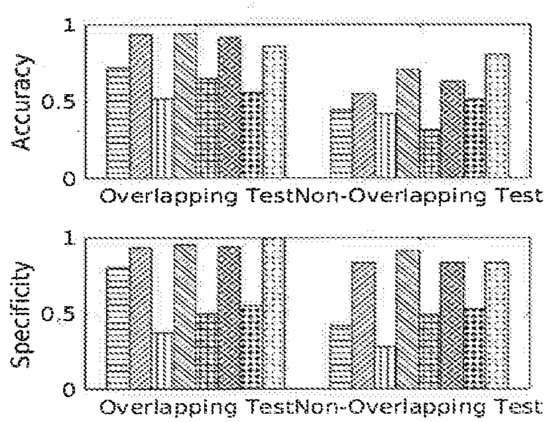

FIG.7C