IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 5 August 2023, accepted 29 August 2023, date of publication 11 September 2023, date of current version 19 September 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3313605

RESEARCH ARTICLE

Intelligent Detection of Adventitious Sounds Critical in Diagnosing Cardiovascular and Cardiopulmonary Diseases

XINGZHE ZHANG, DINESH MADDIPATLA, (Member, IEEE), BINU B. NARAKATHU, (Senior Member, IEEE), BRADLEY J. BAZUIN, (Member, IEEE), AND MASSOOD Z. ATASHBAR, (Senior Member, IEEE)

Department of Electrical and Computer Engineering, Western Michigan University, Kalamazoo, MI 49008, USA

Corresponding author: Xingzhe Zhang (xingzhe.zhang@wmich.edu)

This work was supported in part by Stethographics Inc., under Grant 29-7026050 and in part by the Center for Advanced Smart Sensor and Structure.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Human Subjects Internal Review Board (HSIRB) at Western Michigan University.

ABSTRACT A Multi-Channel Stethograph System (STG system) was designed and developed as an electronic auscultation system for recording heart, lung, and trachea sounds non-invasively through an acoustic sensor array. The STG system consists of 16 acoustic sensors, a signal conditioning board, and a data logger (data acquisition, wireless transmission, sound visualization). The STG system captures breath with any adventitious sound event in 16 locations simultaneously to maximize the information of the specific sound event (for example, detection of the origin of mother adventitious sound and extracting its features), when compared with a single-channel stethoscope. This system can be an efficient tool to aid doctors or physicians in analyzing the adventitious sound from respiration diseases. However, it still requires the need for an experienced doctor or physician in the diagnosis and validation of adventitious sound. This paper presents a computerized method with an intelligent algorithm for detecting various adventitious sounds that are the key characteristics of cardiopulmonary diseases (CD) and assists the doctor/physician in the continuous diagnosis of lungs, which potentially can be beneficial during the COVID-19 progression. The proposed algorithm was able to detect breath patterns using trachea sound; location of the mother adventitious event using lung sounds (14 channels); determine the type of adventitious sound by correlating lung sound with trachea sound. The algorithm consists of breath pattern detection, candidate audio selection, breath pattern extraction, and adventitious sound detection. Digital signal processing techniques such as filtering, windowing, enveloping, discrete Fourier transform, and thresholds were used for identifying and classifying the inhalation and exhalation patterns in the lung sound in an independent (automatic) and intelligent way. The auscultation diagnosis algorithm can identify and distinguish discontinuous adventitious sounds which include wheeze, rhonchi, wheeze & rhonchi, and squawk, with an accuracy of 96.9%, 95.3%, 90%, and 100%. The algorithm was able to fully utilize the advantage of the multichannel system to simultaneously detect breath patterns, types of adventitious sound, and the location of the mother adventitious event that other algorithms cannot achieve. It has the potential to aid doctors/physicians in the early detection and monitoring of any lung disorders by providing objective evidence on adventitious sounds.

INDEX TERMS Stethograph systems, algorithm, coronavirus, acoustic sensors, intelligent, adventitious sounds, lung disorders, wheeze, rhonchi, squawk.

The associate editor coordinating the review of this manuscript and approving it for publication was Tianhua Xu.

I. INTRODUCTION

During the COVID-19 pandemic, the Global Initiative for Chronic Obstructive Pulmonary Disease (COPD) recognizes the necessity of developing innovative and remote approaches to interact with COPD patients [1], [2], [3]. COVID-19 involves a series of acute and atypical respiratory issues that particularly impact adults and elderly people with underlying medical conditions. Previous studies have reported that COVID-19, unlike other respiratory illnesses, can cause lasting lung damage with severe illness, and a lack of targeted therapy remains a challenge. The virus can induce lung complications (cardiopulmonary diseases (CD)) such as pneumonia, COPD, and asthma, identifiable by listening to abnormal lung sounds such as wheeze, rhonchi, squawks, and crackles, resulting from difficulty in breathing and abnormal heart rhythms [3]. These CDs pose significant health and financial burdens in the United States each year [4]. Further, the number of CD patients has increased due to COVID-19. As per the data from 555 US medical centers, a total of 192,550 adults have been hospitalized with COVID-19, and 55,593 of them (28.9%) required ICU admission. In addition, people with pre-existing respiratory disease had a modestly increased risk of severe COVID-19. As a result, detecting and monitoring respiratory diseases have become extremely important, especially for those infected with COVID-19 who are more susceptible to developing respiratory illnesses.

Respiration monitoring has been a critical process in identifying adventitious sounds and diagnosing lung disorders. Continuous respiration monitoring is crucial to understand the lung condition during COVID-19 progression or the severity of the CDs for patients either in ICU or regular wards or at-home treatment. However, currently, there is no equipment available for continuous monitoring of lung condition while providing the details of adventitious sound such as its location, amplitude, and frequency. Stethoscopes have been used mostly by physicians to obtain adventitious sound information and aid in the diagnosis of pulmonary disorders, since the invention of the stethoscope by Laennec in 1816 [5], [6], [7]. The audio obtained from the stethoscopes plays a significant role in providing vital information about the heart, lungs, and trachea (HLT) conditions [8], [9], [10], [11]. But the acoustic information obtained from stethoscopes is often not reliable due to weak lung sound combined with environmental noise. Moreover, it has been a difficult task to extract abnormal or disease-identifying features from the acoustic information to diagnose CDs [12]. In recent years, electronic auscultation recording of HLT audio and the analysis of HLT audio after transferring the acquired signal to a computer has been considered to be a reliable, non-invasive, and inexpensive technique to diagnose lung condition [13], [14]. Even though an electronic auscultation recording system is an efficient tool to aid doctors or physicians in analyzing the HLT sound, it does not have the capability to automatically identify the characteristic features of the adventitious sounds and still requires the need for an experienced doctor or physician in the diagnosis and validation of adventitious sound in the lung. Some of the sophisticated hospitals are equipped with advanced equipment such as computerized tomography (CT) scans and X-ray machines to diagnose lung conditions. However, these equipment exposes the patient to very high dosages of radiation and increases the risk of developing cancer [15]. Moreover, due to the COVID-19 pandemic, there has been a significant gap in the availability of these devices, doctors/physicians, and the number of patients who require them [5], [6], [16], [17]. To cover this gap/disparity, there is a need to develop and employ more accessible at-home devices using novel technology capable of monitoring the lung condition which can be extremely helpful for patients.

Many research works in the literature have used a single digital stethoscope with algorithms in performing auscultation and interpretation of lung sounds to diagnose CDs. The techniques used in the development of algorithms generally consist of time-domain analysis, frequency-domain analysis, and combined time-frequency analysis. These works often use database repositories consisting of processed and filtered audio sets with a high signal-to-noise ratio and strong adventitious sounds [12], [18], [19], [20], [21], [22], [23], [24], [25], [26]. However, these audio sets do not reflect the actual lung audio and the reported algorithms are not feasible for processing raw lung audio in a real-time environment. Also, these algorithms have limited functionality, for example, detection of only one type of adventitious sound capability (simultaneous multiple adventitious sound detection study remains unexplored). They also do not provide any information on the timing of each breathing phase (inhalation and exhalation) which is crucial in the identification of the timing of adventitious sounds. To address this, algorithms developed using signal processing methods were proposed in the past years to identify breathing phases directly from lung sound recordings [27]. However, these methods were heavily dependent on the clarity and amplitude of the lung sound, but they are not applicable to subjects with respiratory diseases in a real-time environment, since the breathing patterns are known to change during the presence of respiratory diseases [12]. In addition, some researchers developed four and eight-channel digital stethoscope systems, however, these systems process the entire data from all the stethoscopes instead of extracting the required information and discarding the unnecessary data [28], [29], [30], [31]. This increases the processing time and complexity of the algorithm resulting in low efficiency and less accuracy. In addition, the probability of recording/capturing the strongest and most appropriately located adventitious sound (later referred to as the mother sensor) is less with these systems.

In this work, a MATLAB-based auscultation diagnosis algorithm was developed to analyze and identify the adventitious sounds from the recorded heart, lung, and trachea (HLT) audios (16 audios acquired by 16 acoustic sensors) of a Multi-Channel Stethograph System. The algorithm consists of breath pattern detection, candidate audio selection, breath pattern extraction, and adventitious sound detection which is novel when compared to other reported works [28], [29],

[30], [31]. It was developed using digital signal processing techniques such as filtering, windowing, enveloping, and discrete Fourier transform (DFT), and thresholds were used for identifying and classifying the inhalation and exhalation patterns in the lung sound. The algorithm has the capability to provide information on the location/origin of the mother adventitious event and, can identify and distinguish discontinuous adventitious sounds which include wheeze, rhonchi, wheeze & rhonchi, and squawk, simultaneously. This algorithm acquires the adventitious sound information more objectively in an independent (automatic) and intelligent way and process it with greater accuracy, and provides the status of the lung condition and assists the doctor/physician in the treatment.

II. METHODS

A. CLASSIFICATION OF ADVENTITIOUS SOUNDS

Respiratory sounds can be divided into normal and adventitious/abnormal categories according to their acoustic properties. Normal sounds include the sounds generated by breathing in a healthy and properly functioning lungs, airways and trachea. Adventitious sounds are the noise generated during the respiration of the improper functioning lungs, and it is divided into continuous and discontinuous adventitious sounds depending on their duration and mechanism [4], [5], [6], [7], [8]. Continuous adventitious sounds have a time duration >50 ms and are further subdivided into wheeze, rhonchi, and squawk, the common adventitious sounds found in multiple CDs. Discontinuous adventitious sounds have a time duration <50 ms and are divided into fine, medium, and coarse crackles. CDs can be identified by monitoring continuous adventitious sounds from the HLT of the patients [32]. The scope of this paper focuses on developing and implementing an algorithm to detect continuous adventitious sounds since algorithms for detecting discontinuous adventitious sounds have been well-developed by previous researchers [16], [33], [34], [35], [36], [37], [38], [39], [40]. In addition, continuous adventitious sounds require both time and frequency domains for recognizing the patterns (which is difficult and complex), whereas discontinuous adventitious sounds require only time domain analysis.

Wheeze is a high-pitched coarse sound that is often generated when the air passes through inflamed lung airways during respiration. Wheeze has a time duration of >250 ms and a frequency above 300 Hz [33], [34], [35], [36]. The most common cause of recurrent wheezing is asthma and COPD (mostly in exhalation) [33], [34]. Figure 1(a) shows the example of the spectrogram of the lung sound with wheeze. Rhonchi is a low-pitched rattling sound generated due to obstruction or secretions in the narrower airways of the lung. Rhonchi also has a time duration >250 ms and a frequency between 150 to 250 Hz [16], [36], [37], [38], [39]. Typically, it appears in patients with asthma, COPD, bronchiectasis, pneumonia, chronic bronchitis, and cystic fibrosis [37], [38]. Figure 1(b) shows the example of the spectrogram of the lung sound with rhonchi. Squawk is a short sound which is otherwise called as a short inspiratory wheeze generated when the air passes through fluid in the air sacs [40]. Squawk has a pattern with a time duration of 50 to 100 ms and a frequency between 200 to 800 Hz and is commonly associated with pneumonia and pulmonary fibrosis disorder (Fig. 1(c)) [40].

B. MULTI-CHANNEL STETHOGRAPH SYSTEM

A Multi-Channel Stethograph System (STG system) was designed and developed as an electronic auscultation system for recording heart, lung, and trachea (HLT) sounds non-invasively through a set of 16 acoustic sensors as mentioned in our previous work (Fig. 2(a)) [41], [42]. Among the 16 acoustic sensors, 14 were incorporated into a foam pad to cover the maximum size of the lung (to capture the origin adventitious sound accurately), and two were placed directly on the heart and trachea, to acquire sounds simultaneously from the lungs, heart, and trachea. The sounds acquired from the 16 acoustic sensors are sent to a custom-designed 16-channel signal conditioning PCB for filtering and amplification of the 16 acoustic signals. A National Instruments (NI) 9205 data acquisition device (DAQ) consists of an A/D converter as well as a digital multiplexer. The DAQ was used to convert the analog acoustic signals to digital and acquire and transmit the data wirelessly from the 16-channel PCB to a Wi-Fi-enabled device such as a PC/tablet. A LabVIEW-based software application was developed on the Wi-Fi-enabled PC/tablet to record the digital sound signal from the DAQ.

The foam pad with 14 acoustic sensors will be placed behind the back of patients and 2 acoustic sensors will be placed directly on the heart and trachea to acquire sounds simultaneously from the heart and trachea. The HLT sounds of a patient will be recorded for a time duration of 20 seconds and the processed signals (from 16 acoustic sensors) will be saved as an audio set using the LabVIEW program on a Wi-Fi-enabled device. Therefore, one audio set consists of 16 HLT audios where each audio corresponds to 20 seconds of sound data with a sampling rate of 8000.

C. AUSCULTATION DIAGNOSIS ALGORITHM

For algorithm development, testing, and validation, a total of 440 audio sets of HLT sounds were recorded from verified patients by Stethographics Inc (Note: each audio set includes 16 audios (14 audio for lung sound, 1 audio for heart sound and 1 audio for trachea sound).

The methodology/workflow for the detection of adventitious sounds that are critical in diagnosing CCDs is shown in Fig. 2(b). The algorithm detects and analyzes continuous adventitious sounds that include wheeze, rhonchi, and squawk in the lungs using MATLAB. The proposed algorithm consists of 4 stages. The first stage is identifying the location of inhalation and exhalation from trachea audio based on the thresholds and criteria set in the time domain. The next stage is the candidate audio selection (determining the audio with the highest amplitude calculated based on the RMS value from 14 lung audios) among the 14 lung audios. In the third

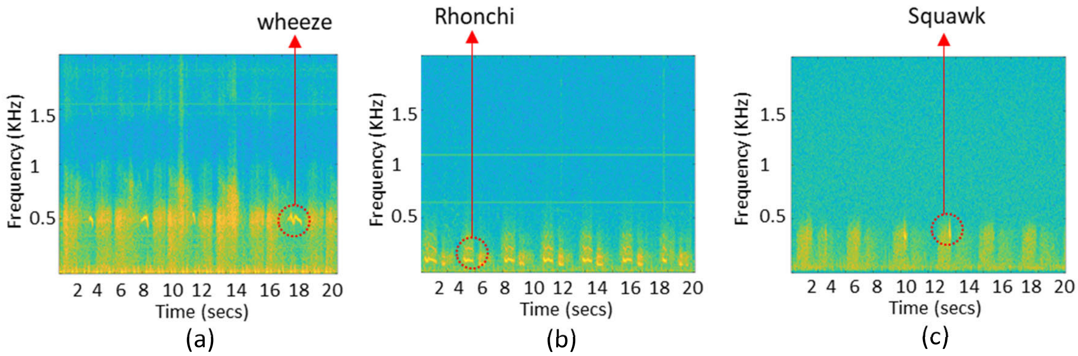

FIGURE 1. Spectrograms showing different adventitious sounds: (a) wheeze, (b) rhonchi and, (c) squawk.

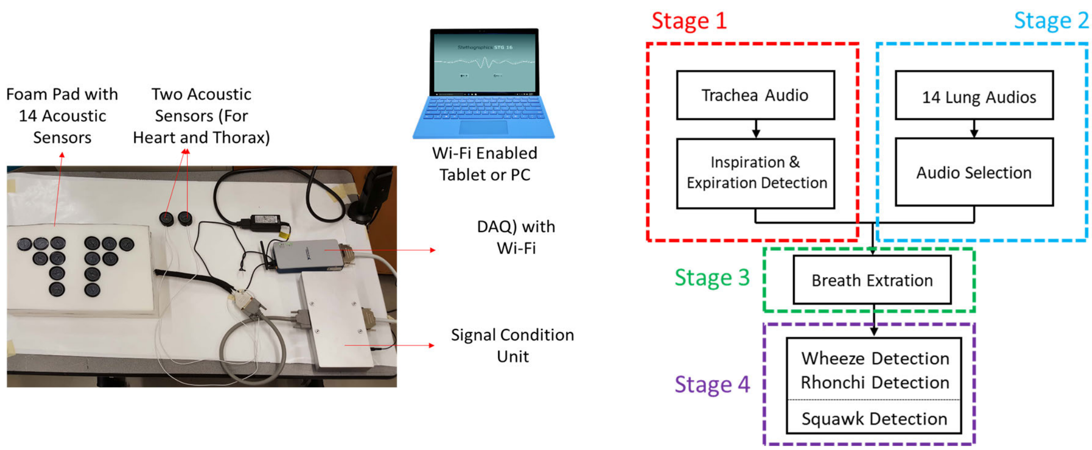

FIGURE 2. (a) Multi-Channel Stethograph System, (b) algorithm procedure.

stage, extract the inhalation and exhalation data from the candidate audio (for the data processing in the next stage) based on the timing of the inhalation and exhalation in trachea audio and disregard the rest of the data in the lung audio for relatively faster and accurate processing of data when compared to processing of complete lung audio. The last stage is the data processing of lung audio for identifying/detecting the continuous adventitious sounds. The major technique employed for the analysis of the lung sound is based on digital signal processing techniques including finite impulse response (FIR) filter, common filter, DFT, hamming window, rectangular window, threshold-crossing, and peak detection. Also, the other techniques that were used in detecting adventitious sounds include linear systems, state-space, multivariate statistics, estimation theory, and nearest neighbor. This methodology employs several of these techniques to detect wheeze, rhonchi, and squawk from the extracted lung audio.

III. RESULTS

A. INHALATION AND EXHALATION DETECTION (STAGE 1)

Typically, adventitious sound events only occur during the inhalation and exhalation events of the lung [17], [37]. Thus, the sound data from the events of inhalation and exhalation is very significant and must be extracted while the rest of the data in the lung audio is discarded. This data reduction process increases the speed and efficiency of the algorithm in analyzing and detecting/capturing essential adventitious sounds. The researchers have been attempting to identify and extract inhalation and exhalation data only from lung sounds [28], [29], [30], [31]. However, lung sound is a low-pitch, low-amplitude signal combined with muscle and cardiovascular noises resulting often in a low signal-to-noise ratio. Therefore, detection of the respiration cycle and identifying inhalation and exhalation is very challenging and inaccurate. In contrast to lung sound, the trachea sound is relatively clear with high amplitude (louder) and better SNR since the adventitious sounds originate in the lungs [43]. This facilitates easy identification of inhalation and exhalation events using the trachea sound. Since, the recording of lung and trachea sounds occurs simultaneously and for the same duration, the inhalation and exhalation data of the lung sounds can be identified and extracted based on the timing information of the inhalation and exhalation event in the trachea sound. The block diagram of respiration/breath pattern detection from trachea sound is shown in Fig. 3. The algorithm consists of pre-processing, signal transformation, feature extraction, and classification.

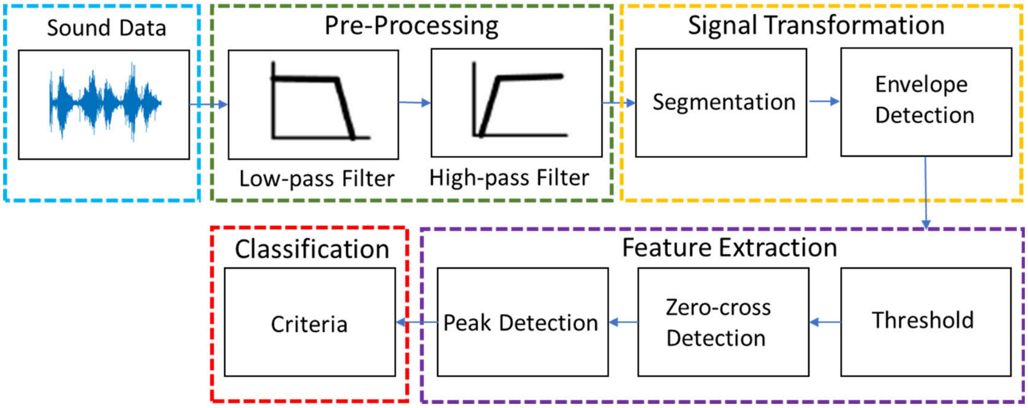

FIGURE 3. Algorithm procedure for inspiration & expiration detection.

Pre-Processing: The pre-processing of the trachea sound data includes the filtering using a band-pass Butterworth filter (100 - 600 Hz) applied forward on the signal segments and then backward to allow zero time and phase delay [reference filtfilt from MATLAB] while eliminating out of band (non-informative signal) noise.

Signal Transformation: This step aims to create a clear trace of breath pattern to limit the influence of impulse noise and data size. It is implemented by segmentation and envelope techniques using a hamming window (Eq. 1 and 2) with size 400 (at 8000 samples per second) and 50% overlapping, applied to the absolute value of the trachea signal. This results in the conversion of the signal to a smooth curve in time waveform.

$$w(x) = 0.54 - 0.46\cos(2\pi)\frac{x}{N}, \quad 0 \leq x \leq N. \tag{1}$$

$$t(n) = \frac{1}{N}\sum\nolimits_{i=0}^{N-1} w(i) \cdot |h(n \pm i)| \tag{2}$$

where N is the length of the window, w(x) is the coefficient of a Hamming window, h(x) is the amplitude of trachea sound and t(n) is the amplitude of the signal after transformation.

Feature extraction and classification: Feature detection was described in detail in our work [42]. In short, the smooth curve of the trachea signal was then analyzed by using a combination of threshold, zero-cross, and peak detection. With respiration estimation, respiration sound classification, and classification refinement, duration and location of inhalation and exhalation can be performed.

B. CANDIDATE AUDIO SELECTION (STAGE 2)

Any adventitious sound event can be detected by at least one of the 14 acoustic sensors located on the chest that covers the maximum area of the lungs. The acoustic sensor close to the origin of the adventitious sound will have the highest signal amplitude and is called the mother adventitious sound which provides information on the location of the infection area/disease. The audio of the adventitious sound can also be recorded by the other nearby acoustic sensors, however, the amplitude of the adventitious sound reduces, depending on the location and distance of the acoustic sensor from the origin of the adventitious sound. The adventitious sounds with reduced amplitudes recorded by other acoustic sensors away from the origin are called daughter adventitious sounds [44]. Figure 4(a), (b), and (c) shows the location of each acoustic sensor placed on the body and their corresponding sound waveforms in the time domain, respectively. A Root Mean Square (RMS) computation is applied to the lung sounds for calculating the average amplitude as it is a useful method when the random noise-related input variables in the data are negative and positive, especially for sinusoids. The signal with the highest RMS represents the mother adventitious audio signal. Equation 3 shows the calculation of the average magnitude based on the signal energy (E, unit - amplitude):

$$E = \sqrt{\frac{1}{N}\sum_{1}^{N}(x[t])^2} \tag{3}$$

where N is the total number of samples, x[t] is the amplitude at time sample t. Detection of the mother adventitious/the location of the disease can be identified using the location of the sensor (that provided the signal with the highest RMS) placed over the chest (Fig. 5(a)). Also, for accuracy and efficiency purposes, instead of analyzing all the lung audios (14 audios), the audio signal with mother adventitious has been selected for detecting the adventitious sound event and is termed as a ‘‘candidate audio signal’’. Only the candidate audio signal was used for further analysis in this paper.

C. BREATH PATTERN EXTRACTION (STAGE 3)

Breath pattern extraction is a pre-processing stage for adventitious sound detection, it detects, filters, and formats segments of the audio signal to enhance the signal quality and data processing efficiency. In the detection step, a linear phase impulse response of a digital bandpass filter with cutoff frequencies of 50 Hz and 800 Hz with zero phase was used to allow the desired frequency components (between 50 to 800 while it filters the white noise and unwanted signals from the audio [44], [45]. In the segment formatting step, the breath pattern (inhalation and exhalation) is identified

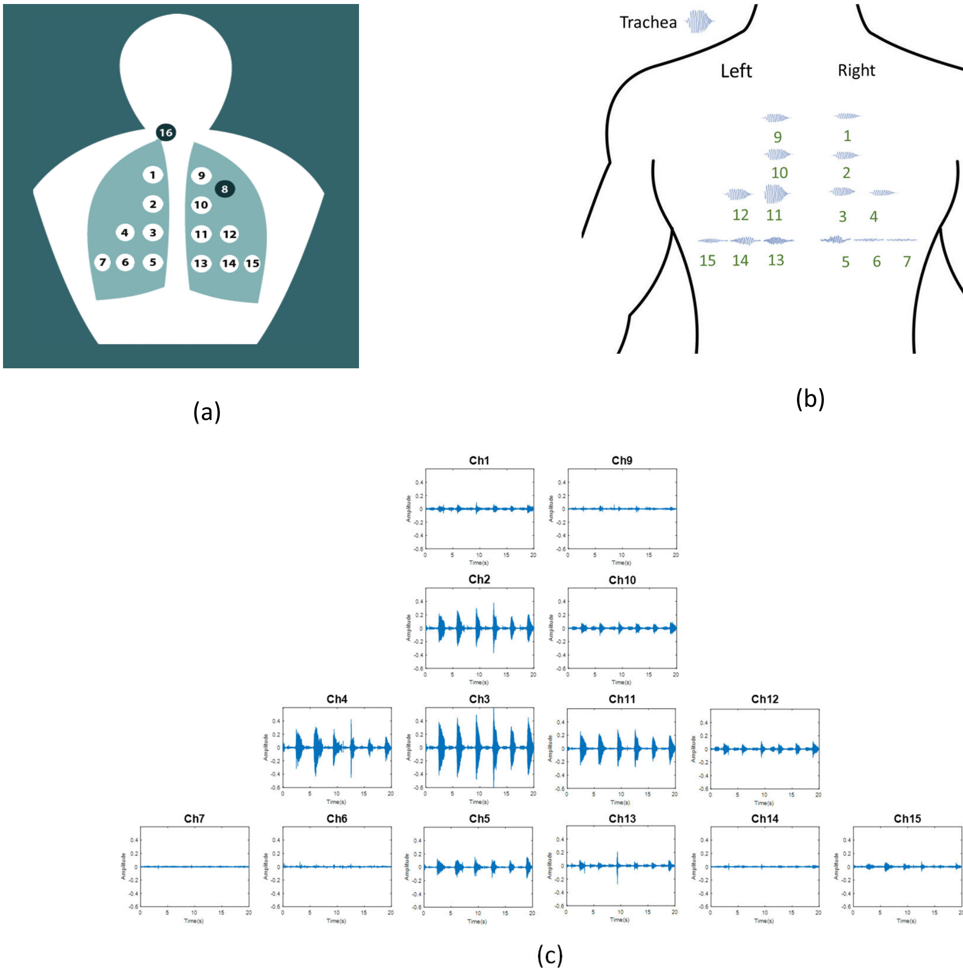

FIGURE 4. **(a) Location of the acoustic sensor array, (b) Sound transmission through the lung, (c) time domain sound waveform distribution.**

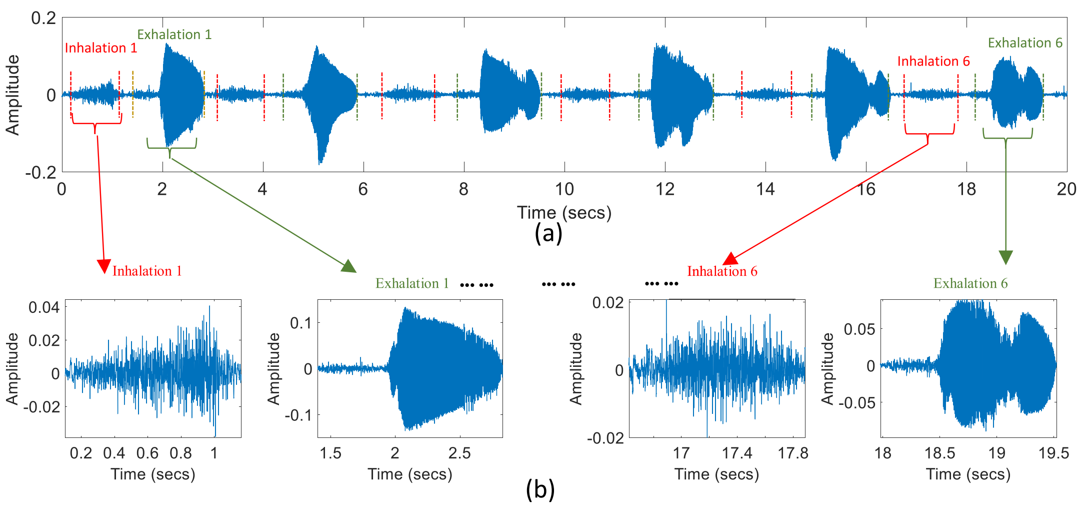

FIGURE 5. **(a) candidate audio signal and (b) extracted inhalation and exhalation signal.**

and extracted from the candidate audio signal based on the respiration information detected from the trachea sound. The rest of the signal (other than the inhalation and exhalation pattern) is eliminated to improve the accuracy and efficiency of the system since the adventitious sounds occur only during the inhalation and exhalation. Figure 5 shows an example of the inhalation and exhalation signal recognized and extracted from the candidate audio signal.

D. WHEEZE, RHONCHI, AND SQUAWK SOUND DETECTION (STAGE 4)

1) WHEEZE AND RHONCHI SOUND DETECTION

Wheeze and rhonchi are continuous sounds with similar time duration (in the time domain) but different frequencies (in the frequency domain). An algorithm (Fig. 6) is developed with the functional characteristics of detecting wheeze and rhonchi based on time duration and dominant frequency analysis being simultaneously performed (creating a time-frequency representation of the sound signal). The algorithm consists of signal transformation, feature extraction, and classification of adventitious sound.

a: SIGNAL TRANSFORMATION

Signal transformation involves segmentation and DFT of extracted inhalation and exhalation signals of candidate audio signal, to convert them into time-frequency representation, similar to a digital channelizer [46]. A time–frequency representation aids in the analysis of a signal represented over both time and frequency simultaneously to describe the frequency components of time-varying signals which can be used for the detection of wheeze and rhonchi. Segmentation is a process that splits high-dimensional vectors of the extracted pattern into several low-dimensional vectors (frames) and captures their detailed characteristics in terms of time and frequency. This process is implemented by processing narrow time segments (50 ms width) with overlapped (50%) periods using a Hamming window function (Fig. 7). This operation is a digital channelizer, filtering and decimating the audio signal into a defined number of bandpass frequency regions (DFT bins) that are produced at a decimated rate from the original audio.

A DFT was used to convert the segmented frames (in the Hamming window) (Fig. 7) into frequency domain bins (Fig. 8(a)) (discrete-time data converted to discrete frequency data) using Eq. 4. In other words, DFT acquires the frequency content of the segmented frame as it changes over the time segments processed and enables visualizing the signal as a 2-D function of time and frequency.

$$X(m, k+1) = \sum_{n=0}^{N-1} x(n+m \cdot M+1)e^{-j2kn\pi/N} \tag{4}$$

where x(n) is the segmented frame and X(m,k) is the converted signal (time segmented frequency domain), k is representing the frequency domain ordinal, n is the time domain ordinal, N is the length of the window (Fig. 8(a)), and M is the time sample offset of each segment. The converted signal (time-frequency domain) provides useful information such as frequency, time length, and strength of a continuous abnormal sound.

b: FEATURE EXTRACTION

The feature extraction includes frequency band selection and peak detection to extract potential information or key characteristics of the wheeze/rhonchi sound in each inhalation/exhalation signal. In the frequency waveform of one segmented frame (Fig. 8(b)), the frequency axis is split into 3 frequency bands, 50 - 150 Hz (Band I), 150 - 250 Hz (Band II), and 300 – 600 Hz (Band III). As specified in the literature, the dominant frequency of rhonchi falls in the 150 - 250 Hz frequency band, wheeze in the 300 – 600 Hz band, and normal breath (considered as reference) in the 50 – 150 Hz band [43]. Therefore, different magnitude criteria (wheeze and rhonchi) can be defined to detect the peaks in the predefined three frequency bands of the waveform.

Peak detection is a method in digital signal processing to detect the dominant frequency of the signal in the segmented frame. When the peak (highest amplitude) is identified (Preference (Band I), Prhonchi (Band II) and Pwheeze (Band III)), its dominant frequency is marked as "$*$" (Fig.8) and this procedure is repeated for each segmented frame to obtain the peaks of all the frames.

c: CLASSIFICATION OF THE DETECTED PEAKS AS WHEEZE AND RHONCHI

A set of criteria is applied to examine the detected peaks in mainly 5 Steps, for detecting the wheeze and rhonchi characteristics. These main criteria include:

- *Local maxima*: Obtain the amplitude of Preference, Prhonchi, and Pwheeze.
- *Peak coexistence*: The amplitude of each of the Pwheeze and Prhonchi should be greater than the amplitude of Preference and if not, discard the peak that is lower than the Preference. If both the Pwheeze and Prhonchi are greater than the Preference, then the peak with a smaller magnitude (between the Pwheeze and Prhonchi) should be greater than half of the other (largest) peak, otherwise discard the smaller magnitude peak.
- *Grouping*: Peaks from all the segmented frames in the same frequency band are considered to be part of the same wheeze/rhonchi if the frequency difference between the peaks that belong to subsequent frames is no more than 50 Hz.
- *Reforming*: Calculate the average frequency of the peaks in one group for wheeze/rhonchi identification. The peaks group in Band II is considered a potential rhonchi and the peaks group in Band II is considered a potential wheeze.
- *Time Continuity*: The total time duration of each peak group should be greater than 250 ms. If the time duration of each peaks group is greater than 250 ms in Band II, the person is confirmed with rhonchi and if it is in Band III, the person is confirmed with wheeze.

These criteria are repeated for each inhalation/exhalation signal. Analyzed results from all of inhalation and exhalation signals will be recombined sequentially to reform the 20s sound signal in the time-frequency representation. An example of a signal containing a wheeze is shown in Fig. 8(d). In Band II, the group gradually formed by peaks with a duration greater than 250 ms were wheeze. Similarly,

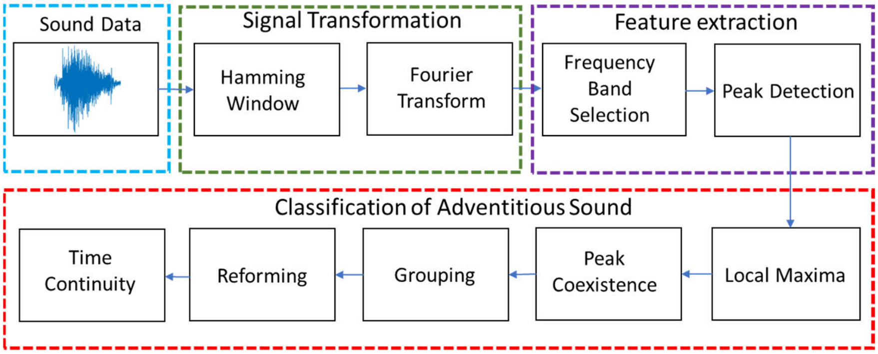

FIGURE 6. Algorithm for Wheeze/Rhonchi detection.

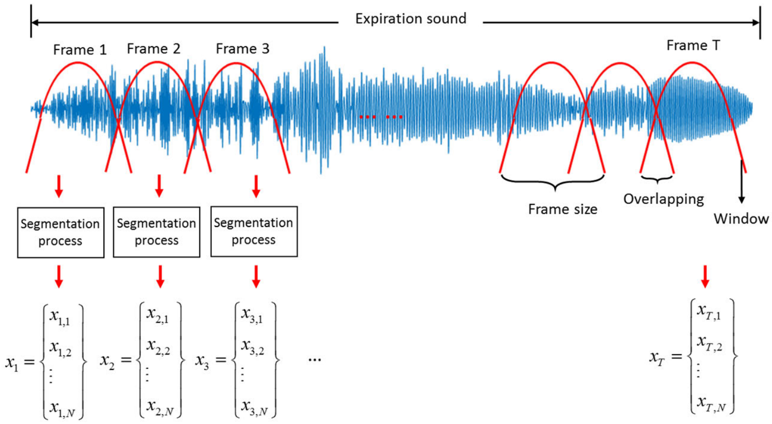

FIGURE 7. Waveform segmentation.

Fig. 8(e) shows the example of a signal containing rhonchi, where the peaks group duration in Band I was observed as greater than 250 ms.

2) SQUAWK SOUND DETECTION

Squawk is defined as a short continuous adventitious sound which is also called as a short inspiratory wheeze. Only inhalation is required for the detection of a wheeze since it appears only during inhalation (hence, called as short inspiratory wheeze). The detection algorithm for squawk follows the algorithm of wheeze and rhonchi detection. Since the duration of the squawk is very short (50 ms to 100 ms), a relatively higher resolution is required in the segmentation stage. Each of segment frame was further split into 5 subframes using a narrower hamming window with a 10 ms duration. After feature extraction and classification, peak groups with duration from 50 – 100 ms and frequency band from 200 - 800 Hz are considered as squawks. Figure 8(f) shows the pattern of squawk in the time-frequency domain of lung sound (since the time duration is 70 ms and frequency is 280 Hz).

IV. DISCUSSION

The developed algorithm was implemented using MATLAB on a Microsoft® Surface laptop for evaluating its performance to detect wheeze, rhonchi, and squawk events. A total of 440 verified audio datasets were utilized. These datasets were recorded by Stethographics, Inc. from patients with pneumonia, COPD, and asthma at Faulkner Hospital, Boston, using the stethograph prototype system. Among the 440 datasets, 220 sets contain wheeze events, 130 sets have rhonchi events, 20 sets have both rhonchi and wheeze events and 30 sets have squawk events. The remaining 40 sets have normal breath sounds without any adventitious sound events. To build the algorithm, 20 datasets of wheeze, 20 sets of rhonchi, and 10 sets of squawks were selected from the 440 datasets. For testing the developed algorithm, all 440 datasets were used for evaluation. The algorithm developed to detect various adventitious sounds was characterized in terms of sensitivity (SE), specificity (SP), and accuracy (ACC) using Eq.5 to 7, respectively [47].

$$SE(\%) = \frac{TP}{TP + FN} \times 100 \tag{5}$$

$$SP(\%) = \frac{TN}{TN + FP} \times 100 \tag{6}$$

$$ACC(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{7}$$

where TN, TP, FN, and FP indicate the true negative, true positive, false negative, and false positive values, respectively. TP indicates if a specific adventitious sound event was

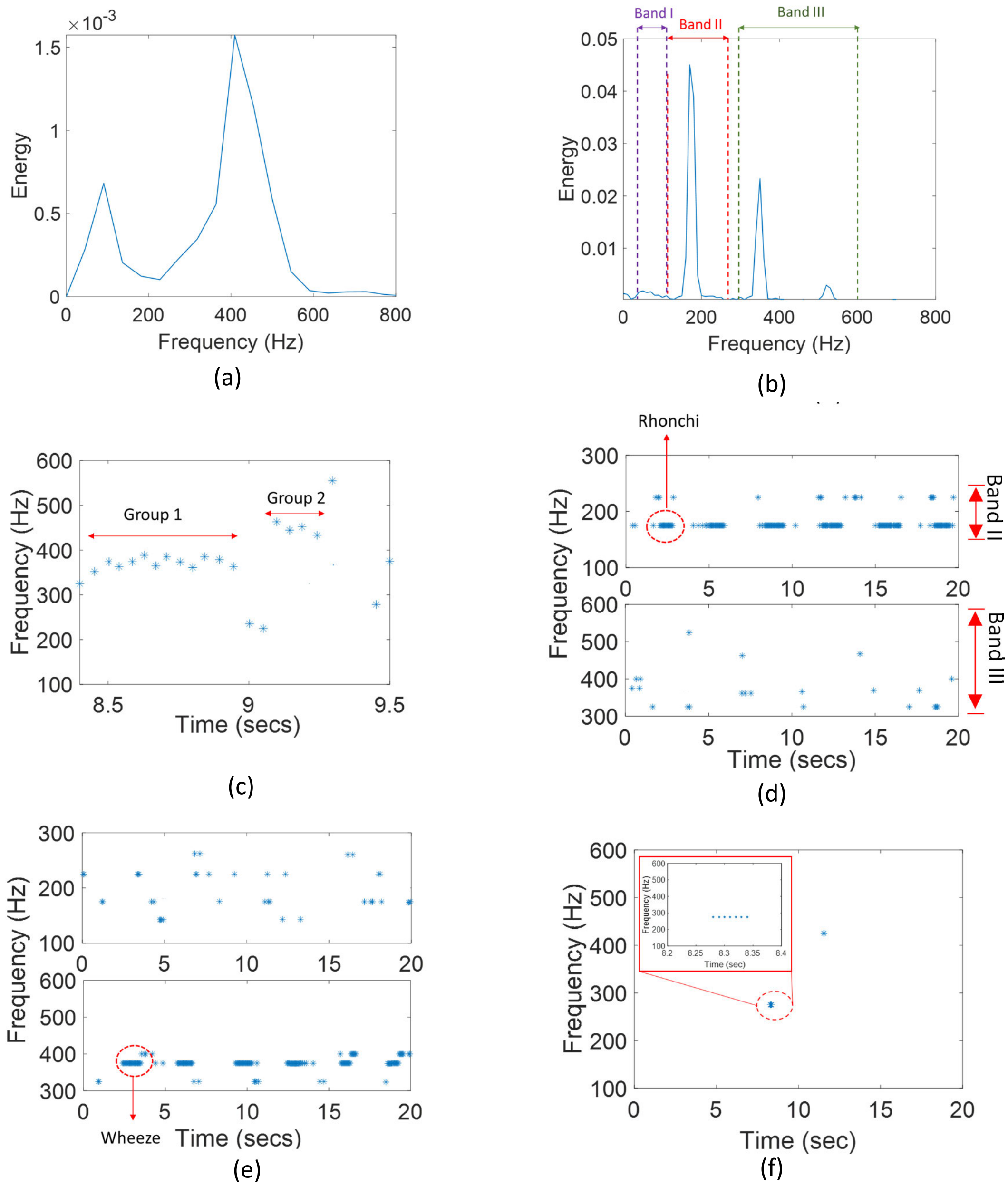

FIGURE 8. (a) Frequency waveform of one segmented frame obtained using DFT, (b) distribution of frequency bands in frequency waveform, (c) peak group in time-frequency representation of one respiration cycle (23 segmented frames), and time-frequency representation of the characteristic audio signal showing the (d) Rhonchi and (e) Wheeze (f) squawk.

correctly detected. FP denotes if a normal respiratory sound event was incorrectly detected as a specific adventitious sound event. TN provides information on whether a normal respiratory sound event was correctly detected. FN denotes if a specific adventitious sound event was incorrectly detected as a normal respiratory sound event. In simple terms, SE represents "the ability of a test to correctly identify patients with a disease", SP provides the information on "the ability of a test to correctly identify people without the disease" and ACC represents "the ability to differentiate the patients with and without disease correctly" [48].

All 440 audio datasets utilized in this study were verified samples obtained from the Faulkner Hospital, Boston. The patient lung conditions and infection locations were collected based on the patient's diagnosis history. The presence of adventitious sound events was verified by the medical professionals in the hospital through auditory and visual examination of the sounds. Then, a datasheet with comprehensive information about each audio dataset, including the patient's lung condition and the presence of wheeze, rhonchi, and squawk, was provided by Stethographic, Inc. This datasheet served as the ground truth/gold standard to

TABLE 1. Test results obtained using developed algorithm.

Type of Lung sounds	*No. of Samples*	*Detected Correctly*	SE	SP	ACC
Wheeze	220	212	96.3%	100%	96.9%
Rhonchi	130	124	95.3%	95%	95.3%
Wheeze&Rhonchi	20	18	90%	100%	96.6%
Squawk	30	30	100%	100%	100%

TABLE 2. Comparison of the current system with published literature in terms of functionality.

Reference	No. of digital stethoscopes	Detection of wheeze	Detection of rhonchi	Detection of squawk	Location of adventitious event	Dataset
I. Mazić et al., 2015 [22]	1	Yes	No	No	No	45
J. Torre-Cruz, 2020 [35]	1	Yes	No	No	No	208
J. De et al., 2020 [24]	1	Yes	No	No	No	64
J. E. Earis et al., 1982 [40]	1	No	No	Yes	No	14
K. Kikutani et al., 2022 [50]	1	Yes	Yes	No	No	57
Tripathy et al., 2022 [52]	1	Yes	No	No	No	112
Islam et al, 2018 [53]	4	Yes	No	No	No	60
Guo et al., 2022 [54]	72	No	No	No	Location of heart	N/A
This work	16	Yes	Yes	Yes	Yes	440

evaluate the developed algorithm's accuracy in detecting the adventitious sounds present in the datasets.

Table 1 shows SE, SP, and ACC results for wheeze, rhonchi, wheeze & rhonchi, and squawk to evaluate the robustness of the developed algorithm in detecting the adventitious sound events. The performance of the wheeze detection has a SE of 96.3%, SP of 100%, and an accuracy of 96.9%, since eight samples were not correctly detected out of 220 samples. The algorithm was not able to detect the wheeze from the eight samples since the amplitude of the wheeze was too weak (in other words, the wheeze has low energy (dB) with dominant breath sound in the frequency domain). The performance of the rhonchi detection has a SE of 95.3% and ACC of 95.3%. Six samples were not correctly detected out of 130 samples due to weak rhonchi sounds compared to the breath sounds in the frequency domain. An SP of 95% was calculated since two samples out of 40 sets of normal breath sound (no adventitious sound events) were detected with rhonchi due to the dominant frequency of the breath sound observed at 150 to 250 Hz. The performance of Wheeze & Rhonchi detection has an accuracy of 96.6% since the amplitude of the wheeze was too weak when compared to the rhonchi in two samples and therefore only rhonchi has been detected. In 30 sets of HLT sounds with squawk, the algorithm has achieved an accuracy of 100% due to the strong energy and short duration of the squawk sound. The precise original location of the mother adventitious sounds (that potentially linked to respiratory disease) in the patients' left lung or right lung was easily determined. Out of 440 samples, the developed algorithm successfully identified the disease's original location in 429 samples (left or right lung). 11 sets were incorrect because they were insignificant, implying that the sound amplitudes in the left and right lung were similar. The main concern regarding the algorithm evaluation is the limited availability of recorded audio datasets containing multiple adventitious sounds, especially squawk events. Due to this limitation, the number of available audios may not be sufficient to comprehensively assess the accuracy of the algorithm.

The amplitude and frequency of each adventitious event in respiratory sounds which generated in the chest region of human body are different, and the location/origin of sounds can only be detected by simultaneously recording the sounds at different locations of the chest by increasing special resolution [49]. The multi-channels are very critical to detect any potential respiratory disease manifestations at an early stage. The proposed algorithm was able to fully utilize the advantage of the multi-channel system to simultaneously detect breath patterns using trachea sound, and the location of the mother adventitious event using lung sound (14 channels), and determine the type of adventitious sound by correlating the lung sounds with breath patterns from trachea sound. The comparison of the presented algorithm with existing algorithms in terms of functionality is shown in Table 2. As mentioned in the introduction, there are several reports with algorithms developed for detecting lung sounds using 1 - 4 acoustic sensors [12], [18], [19], [20], [21], [22], [23], [24], [25], [26], [28], [29], [30], [31]. However, often they cannot find the origin of the diseases or the location of mother adventitious sounds due to the limited acoustic sensors. In addition, these algorithms do not have the capability to process the audio signal processing efficiently (lacks identifying and extracting necessary information and eliminating/discarding unnecessary data). The advantage of the developed system and algorithm over existing methods is the capability to detect various adventitious sounds using 16 acoustic sensors efficiently (this provides relatively accurate location/origin of the diseases) and intelligently identifies, extracts and characterizes the desired sounds patterns in the lung audio based on the trachea audio and detect the different adventitious sounds effectively.

V. CONCLUSION AND FUTURE WORK

Since detection and monitoring of the respiratory diseases is very critical in diagnosing CDs, the STG system with intelligent algorithms was developed which has capability to condition and transmit HLT sounds simultaneously for detecting various adventitious sounds which are the key characteristics of various CDs [51]. Also, it is envisioned to improve the quality of health care and clinical productivity through faster testing and analysis of HLT sounds, particularly when X-Rays or CT scans are to be avoided. In addition, this system can facilitate at-home diagnosis of various CCDs during the coronavirus progression and remote consultation. The developed algorithm is comprehensive, intelligent, and avoids unnecessary complex classification techniques and models. The algorithm uses the frequency and duration of adventitious sounds as the critical parameters to set the required thresholds for detecting various adventitious sounds. It detects adventitious sounds with a sensitivity of $>90\%$ and a specificity of $>95\%$. This combination of acoustic sensor system and intelligent algorithm can facilitate easy and continuous diagnosis of any lung disorders, which is crucial during the COVID pandemic. In this study, 440 verified audio data sets were utilized to preliminarily evaluate the algorithm and assess its accuracy to detect the adventitious sounds. The robustness of our methodology will be improved by collecting more verified datasets from different patients and validating them using the developed algorithm. Future research is focused on obtaining US Food and Drug Administration (FDA) clearance and conducting very large-scale clinical tests (to improve the algorithm, if necessary; and obtain precise location of the mother adventitious sounds) on patients. In addition, the algorithm will be tested prospectively in a real-life setting to assess both its accuracy and its usability by Personal healthcare workers (HCWs). The algorithm will be updated and refined based on new datasets. This enables potential applications in resource-limited settings in the developing world to assist HCWs in the early diagnosis of CDs.).

ACKNOWLEDGMENT

Statements of ethical approval: The Human Subjects Internal Review Board (HSIRB) at Western Michigan University affirmed that HSIRB approval is not required for conducting this study. Further, all the subjects provided written informed consent, and their personal information was not collected to participate in this study.

REFERENCES

[1] T. F. Lüscher, "The saga continues: Is COVID-19 a cardiopulmonary disease," *Eur. Heart J.*, vol. 41, no. 22, pp. 2041–2044, 2020.

[2] A. Taylor, D. J. Lowe, G. McDowell, S. Lua, S. Burns, P. McGinness, and C. M. Carlin, "Remote-management of COPD: Evaluating the implementation of digital innovation to enable routine care (RECEIVER): The protocol for a feasibility and service adoption observational cohort study," *BMJ Open Respiratory Res.*, vol. 8, no. 1, Aug. 2021, Art. no. e000905.

[3] *Remote COPD Patient Follow-Up During COVID-19 Pandemic Restrictions*. Accessed: Jan. 12, 2023. [Online]. Available: https://goldcopd.org/remote-copd-patient-follow-up-during-covid-19-pandemic-restrictions/

[4] A. D. Lopez, "Chronic obstructive pulmonary disease: Current burden and future projections," *Eur. Respiratory J.*, vol. 27, no. 2, pp. 397–412, Feb. 2006.

[5] A. Araújo, "COPD: From the stethoscope to the spirometer," *Revista Portuguesa de Pneumologia English Ed.*, vol. 23, no. 1, pp. 52–53, Jan. 2017.

[6] A. Roguin, "Rene theophile hyacinthe laennec (1781–1826): The man behind the stethoscope," *Clin. Med. Res.*, vol. 4, no. 3, pp. 230–235, Sep. 2006.

[7] G. Satat, R. Krithika, and R. Ramesh, "Identi-Wheez—A device for in-home diagnosis of asthma," in *Proc. EMBC*, Aug. 2016, pp. 4375–4378.

[8] R. S. Vasudevan, Y. Horiuchi, F. J. Torriani, B. Cotter, S. M. Maisel, S. S. Dadwal, R. Gaynes, and A. S. Maisel, "Persistent value of the stethoscope in the age of COVID-19," *Amer. J. Med.*, vol. 133, no. 10, pp. 1143–1150, Oct. 2020.

[9] M. Klum, "Wearable cardiorespiratory monitoring employing a multimodal digital patch stethoscope: Estimation of ECG, PEP, LVETand respiration using a 55 mm single-lead ECG and phonocardiogram," *Sensors*, vol. 20, no. 7, pp. 2033–2045, 2020.

[10] A. D. de Andrade, T. N. S. Silva, H. Vasconcelos, M. Marcelino, M. G. Rodrigues-Machado, V. C. G. Filho, N. H. Moraes, P. E. M. Marinho, and C. F. Amorim, "Inspiratory muscular activation during threshold therapy in elderly healthy and patients with COPD," *J. Electromyogr. Kinesiol.*, vol. 15, no. 6, pp. 631–639, Dec. 2005.

[11] F. Ponti, A. D. Cinque, N. Fazio, A. Napoli, G. Guglielmi, and A. Bazzocchi, "Ultrasound imaging, a stethoscope for body composition assessment," *Quant. Imag. Med. Surg.*, vol. 10, no. 8, pp. 1699–1722, Aug. 2020.

[12] R. M. Rady, I. M. El Akkary, A. N. Haroun, N. A. E. Fasseh, and M. M. Azmy, "Respiratory wheeze sound analysis using digital signal processing techniques, computational intelligence, communication systems and networks," in *Proc. 7th IEEE Int. Conf.*, Jun. 2015, pp. 162–165.

[13] M. Van Drie and A. Harris, "The stethoscope goes digital: Learning through attention, distraction and distortion," *Gesnerus*, vol. 77, no. 1, pp. 123–148, Nov. 2020.

[14] A. Kandaswamy, C. S. Kumar, R. P. Ramanathan, S. Jayaraman, and N. Malmurugan, "Neural classification of lung sounds using wavelet coefficients," *Comput. Biol. Med.*, vol. 34, no. 6, pp. 523–537, 2004.

[15] M. A. Han and J. H. Kim, "Diagnostic X-ray exposure and thyroid cancer risk: Systematic review and meta-analysis," *Thyroid*, vol. 28, no. 2, pp. 220–228, Feb. 2018.

[16] G. Steinkamp, S. Schmitt-Grohe, G. Döring, D. Staab, D. Pfründer, G. Beck, R. Schubert, and S. Zielen, "Once-weekly azithromycin in cystic fibrosis with chronic *Pseudomonas aeruginosa* infection," *Respiratory Med.*, vol. 102, no. 11, pp. 1643–1653, Nov. 2008.

[17] H. S. A. Roberts, "BTS guidelines for the management of pleural infection," *Thorax*, vol. 59, no. 2, p. 178, 2004.

[18] F. Meng, Y. Shi, N. Wang, M. Cai, and Z. Luo, "Detection of respiratory sounds based on wavelet coefficients and machine learning," *IEEE Access*, vol. 8, pp. 155710–155720, 2020.

[19] C.-H. Chen, W.-T. Huang, T.-H. Tan, C.-C. Chang, and Y.-J. Chang, "Using K-nearest neighbor classification to diagnose abnormal lung sounds," *Sensors*, vol. 15, no. 6, pp. 13132–13158, Jun. 2015.

[20] S. Aras, A. Gangal, and Y. Bulbul, "Classification of healthy and pathologic lung sounds recorded with electronic auscultation," in *Proc. 23rd Signal Process. Commun. Appl. Conf. (SIU)*, May 2015, pp. 252–255.

[21] A. Kevat, A. Kalirajah, and R. Roseby, "Artificial intelligence accuracy in detecting pathological breath sounds in children using digital stethoscopes," *Respiratory Res.*, vol. 21, no. 1, pp. 1–6, Dec. 2020.

[22] I. Mazić, M. Bonković, and B. Džaja, "Two-level coarse-to-fine classification algorithm for asthma wheezing recognition in children's respiratory sounds," *Biomed. Signal Process. Control*, vol. 21, pp. 105–118, Aug. 2015.

[23] B. K. Brew, "A modern approach to identifying and characterizing child asthma and wheeze phenotypes based on clinical data," *PLoS ONE*, vol. 14, no. 12, pp. 1–15, 2019.

[24] J. De, "Wheezing sound separation based on informed inter-segment non-negative matrix partial co-factorization," *Sensors*, vol. 20, no. 9, pp. 2679–2705, 2020.

[25] C. Jácome, A. Oliveira, and A. Marques, "Computerized respiratory sounds: A comparison between patients with stable and exacerbated COPD," *Clin. Respiratory J.*, vol. 11, no. 5, pp. 612–620, Sep. 2017.

[26] C. Pinho, A. Oliveira, C. Jácome, J. Rodrigues, and A. Marques, "Automatic crackle detection algorithm based on fractal dimension and box filtering," *Proc. Comput. Sci.*, vol. 64, pp. 705–712, Jan. 2015.

[27] C. Jácome, J. Ravn, E. Holsbø, J. C. Aviles-Solis, H. Melbye, and L. A. Bongo, "Convolutional neural network for breathing phase detection in lung sounds," *Sensors*, vol. 19, no. 8, pp. 1798–1808, 2019.

[28] G. Altan, Y. Kutlu, and A. Gökçen, "Chronic obstructive pulmonary disease severity analysis using deep learning on multi-channel lung sounds," *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 28, no. 5, pp. 2979–2996, Sep. 2020.

[29] S. Alsmadi and Y. P. Kahya, "Design of a DSP-based instrument for real-time classification of pulmonary sounds," *Comput. Biol. Med.*, vol. 38, no. 1, pp. 53–61, Jan. 2008.

[30] S. Li, "Design of wearable breathing sound monitoring system for real-time wheeze detection," *Sensors*, vol. 17, no. 1, pp. 171–186, 2017.

[31] M. A. Islam, I. Bandyopadhyaya, P. Bhattacharyya, and G. Saha, "Classification of normal, asthma and COPD subjects using multichannel lung sound signals," in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2018, pp. 290–294.

[32] R. Loudon and R. Murphy, "Lung sounds," *Amer. Rev. Respiratory Disease*, vol. 130, no. 4, pp. 663–673, 1984.

[33] N. Barker and E. Heather, "Respiratory sounds: Laryngeal origin sounds," in *Breath Sounds: From Basic Science to Clinical Practice*, 2018, pp. 237–247.

[34] M. H. Brutsche, "Bronchial hyperresponsiveness and the development of asthma and COPD in asymptomatic individuals: SAPALDIA cohort study," *Thorax*, vol. 61, no. 8, pp. 671–677, Aug. 2006.

[35] J. Torre-Cruz, F. Canadas-Quesada, S. García-Galán, N. Ruiz-Reyes, P. Vera-Candeas, and J. Carabias-Orti, "A constrained tonal semi-supervised non-negative matrix factorization to classify presence/absence of wheezing in respiratory sounds," *Appl. Acoust.*, vol. 161, pp. 107188–107202, Apr. 2020.

[36] R. Palaniappan, K. Sundaraj, and N. U. Ahamed, "Machine learning in lung sound analysis: A systematic review," *Biocybernetics Biomed. Eng.*, vol. 33, no. 3, pp. 129–135, Jan. 2013.

[37] N. Sahgal, "Monitoring and analysis of lung sounds remotely," *Int. J. Chron. Obstruct. Pulmon. Dis.*, vol. 6, pp. 407–412, Jul. 2011.

[38] S. Kamble, "Respiratory sound analysis for the diagnosis of respiratory abnormalities," *Sci. J.*, vol. 2, no. 8, pp. 113–123, 2016.

[39] B. Zimmerman and D. Williams, *Lung Sounds*. Treasure Island, FL, USA: StatPearls Publishing, 2020. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK537253/

[40] J. E. Earis, K. Marsh, M. G. Pearson, and C. M. Ogilvie, "The inspiratory 'squawk' in extrinsic allergic alveolitis and other pulmonary fibroses," *Thorax*, vol. 37, no. 12, pp. 923–926, Dec. 1982.

[41] X. Zhang, "Development of a novel wireless multi-channel stethograph system for diagnosing pulmonary and cardiovascular diseases," in *Proc. IMCS*, 2018, pp. 673–674, doi: 10.5162/IMCS2018/P1DH.10.

[42] X. Zhang, D. Maddipatla, B. B. Narakathu, B. J. Bazuin, and M. Z. Atashbar, "Development of a novel wireless multi-channel stethograph system for monitoring cardiovascular and cardiopulmonary diseases," *IEEE Access*, vol. 9, pp. 128951–128964, 2021.

[43] W. Xie, P. Gaydecki, and A.-L. Caress, "An inhaler tracking system based on acoustic analysis: Hardware and software," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 11, pp. 4472–4480, Nov. 2019.

[44] S. S. Kraman, "Does the vesicular lung sound come only from the lungs?" *Amer. Rev. Respiratory Disease*, vol. 128, no. 4, pp. 622–626, 1983.

[45] S. S. Kraman and A. B. Bohadana, "Transmission to the chest of sound introduced at the mouth," *J. Appl. Physiol.*, vol. 66, no. 1, pp. 278–281, Jan. 1989.

[46] F. J. Harris, C. Dick, and M. Rice, "Digital receivers and transmitters using polyphase filter banks for wireless communications," *IEEE Trans. Microw. Theory Techn.*, vol. 51, no. 4, pp. 1395–1412, Apr. 2003.

[47] S. Amelia and H. Roberta, "What are sensitivity and specificity?" *Evidence-Based Nursing*, vol. 23, no. 1, pp. 1–4, 2020.

[48] A. Vyshedskiy, R. M. Alhashem, R. Paciej, M. Ebril, I. Rudman, J. J. Fredberg, and R. Murphy, "Mechanism of inspiratory and expiratory crackles," *Chest*, vol. 135, no. 1, pp. 156–164, Jan. 2009.

[49] H. Pasterkamp and D. Zielinski, "The history and physical examination," in *Kendig's Disorders of the Respiratory Tract in Children*. Amsterdam, The Netherlands: Elsevier, 2019, pp. 2–25, 2019.

[50] K. Kikutani, S. Ohshimo, T. Sadamori, S. Ohki, H. Giga, J. Ishii, H. Miyoshi, K. Ota, M. Nishikimi, and N. Shime, "Quantification of respiratory sounds by a continuous monitoring system can be used to predict complications after extubation: A pilot study," *J. Clin. Monitor. Comput.*, vol. 37, no. 1, pp. 237–248, Feb. 2023.

[51] X. Zhang, *Development of Sensor, Sensory System and Signal Processing Algorithm for Intelligent Sensing Applications*. Kalamazoo, MI, USA: Western Michigan Univ., 2021.

[52] R. K. Tripathy, S. Dash, A. Rath, G. Panda, and R. B. Pachori, "Automated detection of pulmonary diseases from lung sound signals using fixed-boundary-based empirical wavelet transform," *IEEE Sensors Lett.*, vol. 6, no. 5, pp. 1–4, May 2022.

[53] M. A. Islam, I. Bandyopadhyaya, P. Bhattacharyya, and G. Saha, "Multichannel lung sound analysis for asthma detection," *Comput. Methods Programs Biomed.*, vol. 159, pp. 111–123, Jun. 2018.

[54] B. Guo, H. Tang, S. Xia, M. Wang, Y. Hu, and Z. Zhao, "Development of a multi-channel wearable heart sound visualization system," *J. Pers. Med.*, vol. 12, no. 12, pp. 2011–2028, 2022.

XINGZHE ZHANG received the B.S. degree in Electronics Engineering from Mapua University, Manila, Philippines, in 2014 and the M.Sc. degree in Electrical Engineering from Western Michigan University, Kalamazoo, USA, in 2017. He got his Ph.D. degree in Electrical Engineering at Western Michigan University, Kalamazoo, USA. He was a full-time research assistant at the Center for Advanced Smart Sensors and Structures, Department of Electrical and Computer Engineering. His research interest includes the design and fabrication of sensor and sensor system, and development of digital signal processing algorithm.

DINESH MADDIPATLA (Member, IEEE) received his B.E. degree in Electrical and Electronics Engineering from Anna University, India in 2013; the M.Sc. degree in Electrical Engineering from Western Michigan University, USA in 2016 and Ph.D. in Electrical and Computer Engineering from Western Michigan University, USA in 2020. He is currently working as Research Associate in the Centre for Advanced Smart Sensors and Structures (CASSS), Western Michigan University, Kalamazoo, USA. He was awarded Technology Transfer Talent Network (T3N) from the State of Michigan, All-University Research and Creative Scholar Award, and Dissertation Completion Fellowship from Western Michigan University. His research interests include all aspects of design, fabrication and characterization of printed electronics focusing on flexible sensor structures, microfluidics, electrochemical sensors, gas sensors and lab-on-a-chip sensing systems. He is serving as a reviewer for more than 35 international journals and has published over 120 refereed journal articles and refereed conference proceedings. In addition, he has published over 15 patents and invention disclosures.

BINU B. NARAKATHU (Senior Member, IEEE) received the B.E. degree in Electronics and Communication Engineering from Visvesvaraya Technological University, Bangalore, India; the M.Sc. degree in Computer Engineering from Western Michigan University, USA in 2009 and the Ph.D. degree from the Department of Electrical and Computer Engineering at Western Michigan University, USA in 2014. From 2015 to 2017, he was a Postdoctoral Fellow with the Sensor Technology Laboratory (STL), Department of Electrical and Computer Engineering, Western Michigan University, USA. He is currently a Research Associate in the Center for Advanced Smart Sensors and Structures (CASSS), Department of Electrical and Computer Engineering, Western Michigan University, USA. His research interests include all aspects of design, fabrication, and characterization of high performance sensing systems, microfluidic devices, lab-on-a-chip for point-of-care testing (POCT), biosensors, bioelectronics, printed electronic devices and BioMEMS devices for applications in the biomedical, environmental and defense industries. He has published over 140 refereed journal articles and refereed conference proceedings. In addition, he has published 10 patents and more than 30 invention disclosures. He is serving as a member of the technical council committee for NextFlex, a DoD funded consortium for Flexible Hybrid Electronics.

BRADLEY J. BAZUIN (Member, IEEE) B.S. degree in electrical engineering from Yale University, New Haven, CT, USA, in 1980, and the M.S. and Ph.D. degrees in electrical engineering from Stanford University, Stanford, CA, USA, in 1982 and 1989, respectively. He was a Research Assistant with the Center for Integrated Electronics in Medicine associated with the Integrates Circuits Laboratory, Center for Integrated Systems, Stanford University, from 1981 to 1988, a part-time MTS and a System Engineer, from 1981 to 1989, a Principal Engineer with ARGO Systems, Sunnyvale, CA, USA, from 1991 to 2000. He has been a Term Appointed Assistant Professor and an Assistant Professor, since 2000, and is currently a Professor of Electrical and Computer Engineering department with Western Michigan University, Kalamazoo, MI, USA. His current research interests include printed electronics, electronic and printed circuit board, circuit design and fabrication, custom integrated circuit design, embedded signal processing, wireless communication, software-defined radios, and advanced digital signal processing algorithms for physical layer communication systems. Dr. Bazuin is a member of the American Society for Engineering Education and the Institute of Navigation.

MASSOOD Z. ATASHBAR (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the Isfahan University of Technology, Isfahan, Iran, in 1989, the M.Sc. degree in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 1992, and the Ph.D. degree from the Department of Communication and Electronic Engineering, Royal Melbourne Institute of Technology University, Melbourne, VIC, Australia, in 1998. From 1998 to 1999, he was a Post-Doctoral Fellow with the Center for Electronic Engineering and Acoustic Materials, Pennsylvania State University, State College, PA, USA. He is currently a Presidential Innovation Professor, a Professor of electrical and computer engineering department, and the Founding Director at the Center for Advanced Smart Sensors and Structures (CASSS), Western Michigan University, USA. He is a Distinguished Faculty Scholar Awardee. He has authored or co-authored more than 300 refereed articles, refereed conference proceedings, and four book chapters. In addition, he has more than ten patents and 35 intellectual disclosures. His research interests include physical and chemical sensor development, wireless sensors, and nanotechnology applications in sensors and flexible hybrid electronic devices.

Dr. Atashbar is a NextFlex Fellow and currently serving as the Co-Chair of the Technical Working Group (TWG) for NextFlex, a DoD Funded Consortium for Flexible Hybrid Electronics. He is an Associate Editor for the Frontiers in Sensors Journal and acted as a Guest Editor for a special issue on printed and flexible sensors in the MDPI Biosensors Journal. He also served as an Associate Editor for the IEEE Sensors Journal, from 2006 to 2016.