Mobile Stethoscope and Signal Processing Algorithms for Pulmonary Screening and Diagnostics

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***Abstract*— Pulmonary diseases represent a large disease burden in terms of morbidity and mortality worldwide. For many reasons, including household air pollution and a shortage of trained doctors, this burden is concentrated in the developing world. The standard diagnostic pathway for pulmonary diseases is prohibitively expensive in developing countries, so these diseases are often misdiagnosed or underdiagnosed. To assist doctors and health workers, there is a need to create tools that can automatically recognize specific lung sounds and provide diagnostic guidance. As a first step towards this long-term goal, we have created a low-cost stethoscope and smartphone application to record lung sounds. We discuss problems we encountered with the initial design and demonstrate an improved design that is currently being used in the field. We also demonstrate an algorithm capable of automatic detection of wheeze sounds. The automatic wheeze detection algorithm uses time-frequency analysis and the Short Time Fourier Transform to identify sections of wheezing in recorded lung sound files. Unlike most published sound classification studies, we trained and tested our algorithms using sound data collected from 38 actual patients at a pulmonary clinic in Pune, India. Despite variability in the quality of the data, our algorithm demonstrated an accuracy of 86% for successfully detecting the presence of wheeze in a sound file. This mobile platform and detection algorithm demonstrates an important step in creating an automated platform for the diagnosis of pulmonary diseases in a real-world setting.**

Keywords—stethoscope, pulmonary, lung, sounds, auscultation, mobile, phone, diagnostics, machine learning, intelligence, algorithms, time-frequency.

I. Introduction

A. Background

Pulmonary diseases, which include asthma, COPD, pneumonia, lung cancer, and tuberculosis, are an increasing global health burden and account for more than 14% of deaths worldwide [1]. More than one billion individuals suffer from chronic pulmonary diseases, which, in addition to causing premature death, reduce the quality of life of those afflicted [2]. This burden falls disproportionately on developing countries because many of the risk factors (e.g. air pollution, biomass or kerosene cook stoves, smoking) for pulmonary disease are highly prevalent in the developing world. The increased prevalence of these diseases is made more harmful by the lack of access to healthcare and affordable tools for screening and diagnosis.

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Fig. 1. Demonstration of mobile stethoscope platform being used for auscultation of subject.

The current standard for pulmonary disease diagnosis is Pulmonary Function Testing (PFT), which requires the use of expensive machines that are operated by specially-trained technicians [3]. These machines include a body plethysmograph, a spirometer, a diffused gas level meter, and an impulse oscillometer. The lack of these machines and trained technicians limits the availability of PFT in the developing world. Instead, in poor resource settings, pulmonary disease diagnosis is typically made by a general practitioner through a subjective analysis of observed lung sounds, symptoms, and the patient's medical history.

Pulmonary diagnostics are further complicated in developing countries by the fact that the majority of practicing general practitioner doctors practice various forms of non-Western medicine, such as Ayurveda and Homeopathy [4]. While diagnosis of cardiac disease is a central part of many schools of medicine, pulmonary disease is often neglected. In addition, hospitals and clinics are overburdened, with insufficient physician staffing to see all available patients, so diagnoses are often made by nurses and pharmacists [5].

B. The Stethoscope

Since its invention in 1816, the stethoscope has been the basic tool for inspecting lung sounds. This tool relies greatly on human senses (sight, sound, and touch) to detect sounds, resonance, and the direction of air flow (inspiration/expiration). The sense of hearing is subject to variability, due to the individual doctor's auditory acuity and the doctor's training to recognize specific sounds. In a study of medical residents in the United States, for example, it was found that internal medicine and family practice residents were only able to identify approximately 80% of wheeze sounds in a series of pulmonary recordings [6].

In wealthier countries, the availability of pulmonary specialists and advanced instrumentation for PFT testing can compensate for a lack of pulmonary diagnostic skills at the primary care level. However, in poorer regions where PFT equipment, technicians, and pulmonologists are not available, errors in auscultation often result in misdiagnosis or lack of early detection of various pulmonary diseases.

C. Electronic Stethoscopes

In order to meet the need for better tools for auscultation, several electronic versions of stethoscopes have been developed, which use of electret microphones [7]–[9] or piezoelectric acoustic sensors[10]–[12]. These devices provide the critical advantage of being able to amplify and record lung and heart sounds. However, the relatively high cost of these devices, combined with the availability of specialty doctors and other advanced instrumentation in wealthier countries has limited the use of electronic stethoscopes in the developed world. Because of the cost, commercial electronic stethoscopes have also been largely absent in developing countries.

The emergence and availability of the smart phone, however, provides an affordable means to implement electronic recordings, conduct sound analysis and transmit recorded sound data.

D. Signal Processing

The ability to record lung sounds allows signal processing and machine learning techniques to automatically analyze the recorded sounds to provide diagnostic support. For over 30 years, a number of different signal processing and machine learning methods have been proposed in the literature for the automated detection of abnormal lung sounds and diagnosis of pulmonary disease [13]–[16]. Many of these methods focus on frequency domain features such as peaks, or compare the ratio of power within certain frequency bands. However, most published methods rely on data from a small number of patients (N<10) and are not clinically validated. In addition, published signal processing algorithms often are not tested on realistic data collected outside the research laboratory, and as a result, are not compatible with lower-quality data collected from inexpensive microphones. Recently, early-stage commercial products have emerged to augment stethoscopes and enhance auscultation with signal processing techniques, but these have been targeted at cardiovascular diseases [8].

II. Implementation

A. Stethoscope Construction

Our mobile stethoscope was constructed by retrofitting a locally-sourced (India) standard stethoscope with a mobile phone "hands-free" microphone. The stethoscope selected was the Micro-Tone model (by Malhotra Surgical Industries), which is sold for approximately US$20 and commonly found throughout India.

A locally-sourced Indian hands-free set (retail price ~US $3.00) was used for recording device with the electret microphone element extended via a wire and embedded at the branching point of the stethoscope pneumatic tube. A photograph of a completed mobile stethoscope is shown in Figure 2.

B. Stethoscope Characterization

To evaluate the stethoscope, we measured its frequency response. Continuous wave sinusoids were generated in

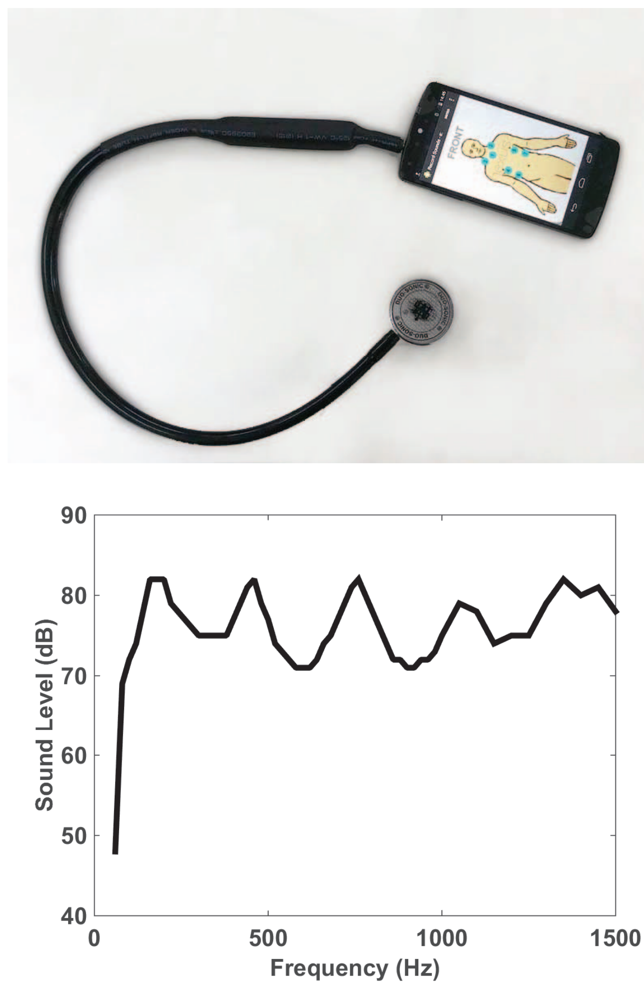

Fig. 2. (top) Photograph of stethoscope model used for clinical study. (bottom) Frequency response of the stethoscope

MATLAB on a PC with frequencies from 60 to 1500 Hz and played through a wide-band Bose Wave Music System. The sound level was measured on the mobile phone using the Android application Sound Level Meter. This application was selected because it is accurate enough to meet OSHA's type 2 instrument standard [17]. An external application was used because it disables the default auto-gain applied to microphones plugged into the Android phone and allows an objective measurement of the sound level. The sound level of the produced sound files was corroborated with a baseline reading from a commercial sound level meter (YFE YF-20), which gave a reading of 80 dB(a) at 500 Hz. The frequency response of the stethoscope is shown in Figure 2.

C. *Mobile Application Development*

We designed an Android application to interface with the mobile stethoscope and record lung sounds for analysis. As shown in Figure 3, the application includes a patient log-in screen and a graphical interface that enables the clinical worker to select a body location and record sounds. Recordings can be captured from up to 11 available locations.

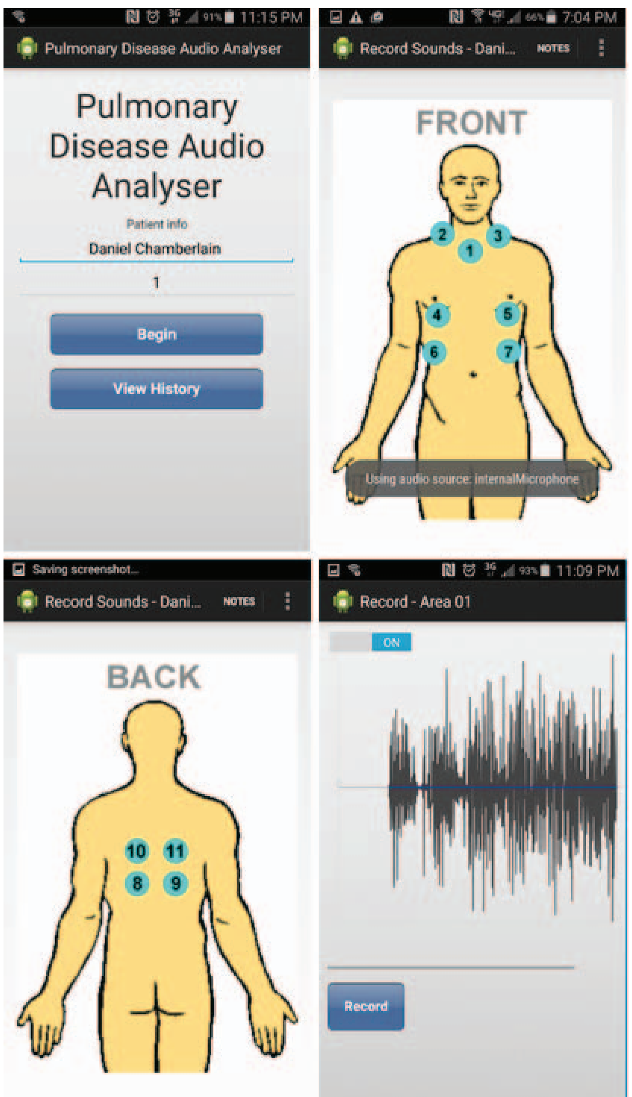

Fig. 3. Screenshots from the data recording mobile application. From the top left are the log-in screen, the recording location selection for both the front and back and a sample real-time waveform plotted as a sound file is recorded.

After the user selects a recording location, the mobile application presents the user with a recording screen that displays a real-time plot of the sounds being recorded by the microphone. Each recorded sound file is twenty seconds long, is sampled at a rate of 44100 Hz, and is saved in WAV format. The user can record and playback sounds multiple times, and select which files to save in the phone memory. The log-in screen is provided for research applications, as it enables multiple patient data to be stored on the phone, indexed by de-identified patient ID numbers.

D. *Signal Processing Algorithm Development*

Signal processing and machine learning algorithms were developed in MATLAB to extract specific features from the lung sounds and identify specific types of abnormal sounds. For the first stage of our study, we focused on wheeze sounds, because it represents the highest incidence among our local Indian population. Based on observations in our clinic, approximately 80% of pulmonary patients with abnormal lung sounds presented with wheezing, 20% with crepitation, and 5% with pleural rub. Some patients presented with multiple abnormal lung sounds.

Our proposed method combines a time-frequency approach for counting wheezes with a machine learning classifier to identify sound files that contain wheezing. Two related algorithms were created and evaluated. An overview of the algorithms is shown in Figure 4. The only difference between the two approaches is the implementation of the local region analysis in step four of the algorithms. We removed the first five seconds of each sound file, because in many cases there was significant noise due the stethoscope motion at the beginning of the recording, as the chestpiece of the stethoscope is placed onto the chest.

The wheeze count algorithms take advantage of the fact that wheezes are sustained harmonic sounds. First, we computed the Short-Time Fourier Transform (STFT) using a Hamming window with a length of 5512 points. This provided a time resolution of 62.5 ms and a frequency resolution of 5 Hz. For each time window in the STFT, we evaluated the power of the maximum peak in the frequency domain between 250 and 800 Hz and divided that by the mean power in the frequency domain between 60 and 900 Hz to compute the Wheeze Power Ratio. The range 250 to 800 Hz was selected because we have found success identifying wheezes using this range in the past. The range 60 to 900 Hz was chosen because it represents most of the sound information in healthy breathing sounds [18]. If the value of the Wheeze Power Ratio exceeded an empirically determined threshold, then that window was labeled as a potential wheeze. For the first algorithm (consecutive algorithm), if sufficient consecutive windows were marked as potential wheezes, then the algorithm identified a wheeze and recorded a wheeze occurrence for that file.

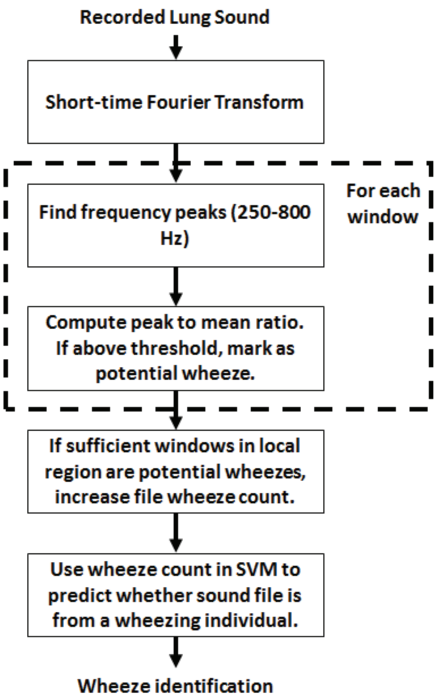

Fig. 4. Overview of the wheeze detection algorithm. Using the STFT result, each window is evaluated to identify prominent peaks in the frequency domain. If enough windows in a local region have prominent peaks, then a wheeze occurence for that file is recorded. Then, an SVM is trained to identify which files contain wheezes based on the number of wheeze occurences.

However, we decided to test a more relaxed constraint to potentially improve performance. Therefore, for the second algorithm (non-consecutive algorithm), if a sufficient proportion of windows in an empirically determined range were marked as potential wheezes, then the algorithm identified a wheeze and recorded a wheeze occurrence for that file.

Finally, a support vector machine was trained to classify sound files as wheeze or healthy, using the number of wheeze occurrences in each file as a predictor. This model takes into account the expected number of false positives per sound file to minimize classification error.

III. Clinical Study and Validation

A. Lung Sound Data Collection

The stethoscope and application combination were used to collect lung sound data from 38 patients at the Chest Research Foundation in Pune, India. Lung sounds were recorded from each of the 11 locations for each patient, which resulted in 418 lung sound files. The bell of the stethoscope was used to record at the trachea and the diaphragm was used for all other locations. Before recording the lung sounds, a pulmonologist (RK) listened to each of the 11 locations for each patient and noted the presence of wheezing or crepitation. Wheezes are high-pitched whistling sounds on expiration, which are indicative of obstruction to expiratory air flow. Crepitation, also called rales, are inspiratory crackle sounds indicative of

Removal Reason	**Percent of removed sound files**
Incorrect stethoscope setup	56%
Stethoscope movement	22%
Faint or no lung sounds	22%

TABLE I. Sound file removal reason. Sound files were assessed for recording quality. For each low-quality file, a reason was recorded. The breakdown of these reasons is shown above.

Lung Area	**Percent with distinct lung sounds**
Trachea	87%
Upper chest	75%
Lower chest	58%
Sides	49%
Lower back	71%
Upper back	72%

TABLE II. Percent of sounds used by area. Sound files were assessed for recording quality. The percent of sound files with sufficient sound quality in each recording region is shown above.

fluid in the lungs. The pulmonologist also noted the patient's body habitus, classifying them as underweight, normal, or overweight.

B. Data Quality Assessment

We reviewed each sound file to ensure that it contained audible lung sounds. Sound files without audible lung sounds were removed from subsequent analysis and labeled with a reason for exclusion.

Of the 418 sound files recorded, 137 were excluded. Of these, 77 sound files had no lung sounds because during the exam, the stethoscope chestpiece was not rotated from the bell position to the diaphragm position after recording from the trachea. This mistake would probably have been prevented if the clinician could hear the sounds in real-time during recording. The remaining exclusion reasons are summarized in Table I.

There was significant variation in the quality of the sound file across the different recording areas (Table II). The trachea and upper chest recording regions had the greatest proportion of good sound files, while the lower chest and sides had the lowest proportion of good sound files. Stethoscope movement that obscured lung sounds was most likely for the side recording regions, with 18% of sounds excluded for that reason. Intermittent or inaudible lung sounds were most prevalent in the lower chest and side regions.

C. Sound File Labeling and Reliability

In order to measure the consistency of the lung sound labeling, the sound files recorded in the clinic where later sent

Auscultation Identification	Sound File Identification		
	Healthy	*Wheeze*	*Crackle*
Healthy	23	4	1
Wheeze	7	19	0
Crackle	1	0	2

TABLE III. Lung sound identification comparison. The pulmonologist initially labeled sound files using traditional auscultation. Then, the sound files were renamed and the pulmonologist listened to each of the sound files and labeled each of the files. The labels from auscultation and the sound files were compared.

back to the same doctor to be re-evaluated a second time. The sound files used for this test were all of the sound files with audible lung sounds from the upper chest recording locations. Each file was given a randomized filename and the doctor was asked to listen to them and note the presence of wheezes and crepitation. These lung sound identifications were then compared to the original labels that were given at the time of recording. These results are summarized in Table III.

Of the 57 sound files that were provided to the physician for identification of adventitious lung sounds, 28 had been previously marked healthy, 26 had been marked as containing wheezes, and 3 had been marked as containing crackles. While the majority of sound files received the same classification as the initial auscultation (77%), there is some discrepancy between the two classifications. Seven patient locations that contained wheezing during auscultation did not have wheezing appreciated in the corresponding sound files. Four patients that had no wheezing during auscultation had wheezing noted on review of their sound files.

D. *Automated Classification Results*

This wheeze classification algorithm was tested on the sound files that were directly labeled by the pulmonologist. These 57 sound files were recorded from the patients' right and left upper chest. The same model was used to identify wheezing in sound files on both sides of the chest.

The results at each step of the consecutive wheeze identification algorithm for one individual are shown in Figure 5. For both algorithms, a large number of potential wheezes were identified and then a smaller subset were found to be wheeze occurrences.

The parameters and results of the two classification algorithms are shown in Table IV. The parameter values were chosen by running a parameter sweep and selecting the parameters that minimized the misclassification rate. For the consecutive algorithm, the potential wheeze threshold was lower, so more potential wheezes were identified than in the non-consecutive algorithm. However, the requirement for consecutive windows then eliminated more of these potential wheezes. The nonconsecutive algorithm outperformed the consecutive algorithm, with a misclassification rate of 14%.

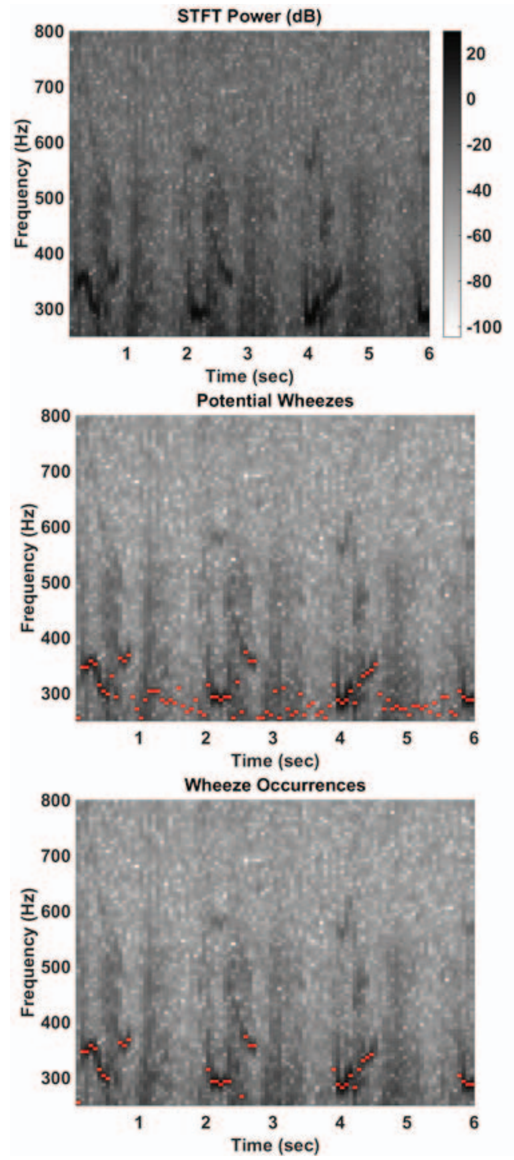

Fig. 5. Sample results of the wheeze detection algorithm. After computing the spectrogram (a), potential wheezes are marked if there are prominent peaks in the correct frequency range. Potential wheezes are shown in red (b). Then, if there are enough potential wheezes in a local region, a potential wheeze is considered a wheeze occurrence. Wheeze occurrences are marked in red (c).

IV. Discussion

The stethoscope and mobile phone application were able to successfully record lung sounds. These lung sound recordings were of high enough quality that when listened to by a pulmonologist, the majority of adventitious sounds heard with traditional auscultation were audible in the recorded lung sound files. While 23% of the recordings were given different labels when the pulmonologist listened to the lung sound files, there did not appear to be a bias in the changed labels. Instead, the sound recordings made it possible to identify some lung sounds that were not identifiable previously and missed some

Algorithm	Wheeze Power Ratio	Number of Windows	Percent of Windows with Wheeze	Misclass-ification Rate
Consecutive	4	4	100%	18%
Non-consecutive	7	5	40%	14%

Table IV. Misclassification rate and parameters for the two proposed algorithms. The best parameters were found for each algorithm to minimize the misclassification rate. The misclassification rate was computed with Leave-One-Out cross validation.

lung sounds that were identifiable previously. This is likely due to the intermittent nature of some lung sounds, which can be audible during one recording but might not be present during a subsequent recording.

These recorded sounds can be used with our automated wheeze detection algorithm. Our best wheeze recognition algorithm has an accuracy of 86%. According to past research on the abilities of different types of physicians-in-training, this identification rate compares favorably with residents in internal medicine and family practice in the US [6]. This is also likely an improvement over the typical performance in the developing world, but we do not have direct comparisons for such an analysis.

Our accuracy results may not be generalizable to situations in which there is less quality control of the recorded sounds. We discarded sound files with inaudible breathing sounds or significant stethoscope movement. As a result, the identification algorithm results may not be directly applicable in some clinical situations, in which there are high levels of background noise or low volume of lung sounds. To address this limitation, we have developed real-time feedback mechanisms for users to assess recording quality, we have increased the sensitivity of the microphone, and we are developing algorithms to automatically remove background noise or request a repeat recording if the sound quality is too low. Additionally, our wheeze classifier was only trained for the upper chest recording locations and might not generalize to other auscultation locations.

While the current implementation of the machine learning algorithm is run in MATLAB software on a PC computer, we are currently implementing versions of this algorithm on the mobile phone platform using the MATLAB Compiler. The ultimate version of this platform will run entirely on the mobile phone.

In the future, this wheeze classifier will be tested on additional data and expanded to identify wheezes in other lung locations. We will investigate combining our wheeze counting method with other wheeze identification methods to improve the accuracy of the final machine learning classification. We will also create classifiers for other abnormal lung sounds. These classifiers will serve as the building blocks for a pulmonary diagnosis platform. In addition to improving and implementing these classifiers, we will investigate combining the current device with a breath sensor so that the presence of abnormal lung sounds can be located within the breath cycle.

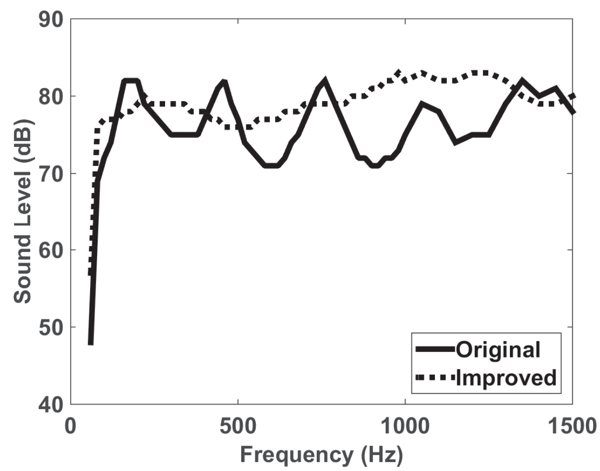

Fig. 6. (top) Photograph of improved stethoscope (bottom) Frequency response of improved stethoscope (dotted line) and original stethoscope (solid line)

V. System Improvements

Our initial stethoscope prototype produced some inaudible lung sounds for two reasons: lack of real-time audio feedback for the recording technician and low sensitivity of the device. In our newest version of the device, we have implemented real-time sound playback in the mobile application so that users are able to listen to the lung sounds as they are recorded. The headphones are modular, so that technicians can use their own headphones and share a stethoscope device or replace broken headphones without needing a replacement microphone and stethoscope. This will eliminate recording errors associated with the wrong stethoscope head setting or lots of movement of the stethoscope head.

The sensitivity of the device was also improved with a new stethoscope design and the use of a different microphone (CUI Inc. CMC-2742WBL-25L). In the new stethoscope design, the microphone location was changed so that the microphone is immediately behind the stethoscope chestpiece. The new device is shown in Figure 6.

We tested the frequency response of the new device and compared it to the frequency response of the original stethoscope. The results are shown in Figure 6. The new device has a flatter frequency response and is more sensitive.

In addition to the improvement of the stethoscope, an additional measurement that would be useful for diagnosis is a determination of the breathing phase. The location of a particular lung sound near the beginning or near the end of inspiration provides information regarding how deep in the airway the lung sound is occurring (upper vs lower airways). The location of a lung sound during inspiration or expiration can also provide clues to a diagnosis. In traditional auscultation, physicians are able to visually ascertain information about the patient's breathing cycle. A mobile phone cannot easily "see" the movement of the patient's chest and mouth or facial expression, particularly in sick patients who have very shallow breathing.

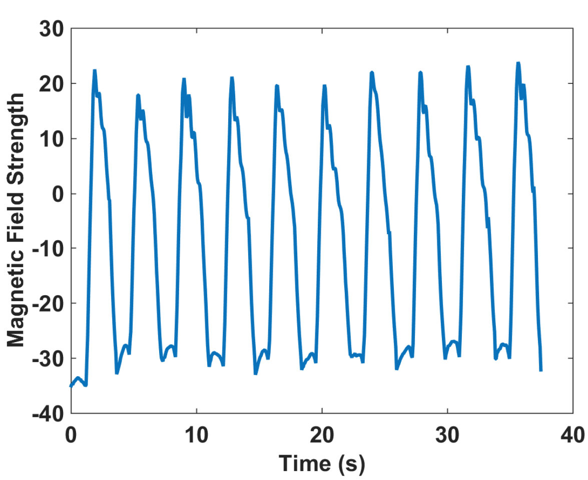

Fig. 7. (top) Photograph of optional breath flow sensor. (bottom) sample data collected on phone showing breath flow cycles.

In order to measure the breathing cycle, we developed an optional breath flow sensor, which was constructed from a tube with a free-standing flap. By embedding a small magnet on the flap, it was possible to make a small magnetic field detector circuit (NVE AAL002) mounted to the tube. (Figure 7). This circuit also contains a USB interface which enabled us to extract the data to the Android phone and record both the acoustic stethoscope data and the breath sensor data simultaneously.

Our improved model of the stethoscope, the application, and the breath flow sensor have been adopted for ongoing data collection in the field.

VI. Conclusions

We have demonstrated the utility of pairing low-cost acoustic stethoscopes with Android devices for the recording of lung sound files. This allows patient's breathing to be analyzed later by additional physicians, remotely using telemedicine, and even enables the use of longitudinal analysis to identify changes in a patient's breathing can be analyzed over time. Once we recorded the sound files, we developed an automated wheeze detection algorithm which was able to successfully discriminate between patients with wheezes or healthy breathing. This work represents a critical step towards the realization of a generalized automated point-of-care platform for diagnosing pulmonary diseases via a mobile phone.

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