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ORIGINAL RESEARCH

A multi-channel acoustics monitor for perioperative respiratory monitoring: preliminary data

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Abstract This study pertains to a six-channel acoustic monitoring system for use in patient monitoring during or after surgery. The base hardware consists of a USB data acquisition system, a custom-built six-channel amplification system, and a series of microphones of various designs. The software is based on the MATLAB platform with data acquisition drivers installed. The displayed information includes: time domain signals, frequency domain signals, and tools to aid in the detection of endobronchial intubation. We hypothesize that the above mentioned arrangement may be helpful to the anesthesiologist in recognizing clinical conditions like wheezing, bronchospasm, endobronchial intubation, and apnea. The study also evaluated various types of microphone designs used to transduce breath sounds. The system also features selectable band-pass filtering using MATLAB algorithms as well as a collection of recordings obtained with the system to establish what respiratory acoustic signals look like under various conditions.

Keywords Tracheal sound monitoring · Lung sound monitoring · Heart sound monitoring · Ventilator acoustic monitoring

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1 Introduction

Monitoring plays an important role in the contemporary management of patients with acute respiratory insufficiency. However, unlike the monitoring of some other organs, monitoring of respiratory function in the critically ill sometimes lacks definition regarding which ‘signals’ and ‘derived variables’ should be prioritized as well as specifics related to timing (continuous vs. intermittent) and modality (static vs. dynamic) [1]. On the other hand, the recovery phase after anesthesia as well as stays in the ICU (intensive care unit) are periods of increased respiratory risk which often benefits from careful monitoring of respiratory performance.

The use of acoustics-based respiratory monitoring for addressing this problem has been matter of interest during the last few decades. Tobin [2] studied respiratory monitoring in the ICU while Brochard et al. [1] published a clinical review regarding respiratory monitoring in the ICU. In another study, Alshaer et al. [3] investigated the monitoring of breathing patterns using a bioacoustics method in healthy awake subjects. He also studied phase tracking of the respiratory cycle in sleeping subjects using frequency analysis of acoustic data [4]. Perioperative respiratory monitoring in anesthesia has been reviewed by Buhre et al. [5] while Mertzlufft et al. [6] investigated perioperative respiratory monitoring of oxygen transport. A bioacoustics method for the timing of respiration during ultrasound-based cardiac studies was introduced by Xiong et al. [7]. Hult et al. [8, 9] presented two bioacoustics methods for the monitoring of respiration, the timing of the different phases of the breathing cycle and for the monitoring of breathing frequency. Finally, Sen et al. [10] introduced a multi-channel device for respiratory sound data acquisition and transient detection. Their system consisted of fourteen microphones attached to the patient's back, an airflow measuring unit, a fifteen-channel amplifier/filter unit connected to a computer via a data acquisition card, and an adventitious sound detection program.

Auditory analysis of respiratory sound signals promises improved detection of certain types of lung diseases. Auscultation of lung sounds (LS) is often the first resource for detection and discrimination of respiratory diseases, such as chronic obstructive pulmonary disease (COPD), pneumonia, and bronchiectasis [11]. With the advancement in computer applications various modern computer-aided techniques are available for lung sound analysis which can assist in the diagnosis of respiratory diseases while minimizing human error due to subjectivity in the interpretation of lung sounds. Computerized analysis of recorded lung sounds, tracheal sounds and breathing sounds may offer a systematic approach to the diagnosis of different respiratory conditions via automated classification of acoustic patterns.

As one of the first researchers in this area, Sankur et al. [12] compared autoregressive (AR)-based algorithms for the classification of lung sounds. They use the AR vectors to build pathological and healthy classes and then designed a classifier to detect pathological conditions. Guler et al. [13] also developed a similar system that performed a two-stage classification of lung sounds while Sahgal [14] design a system with remote respiratory monitoring capability for lung sound abnormality detection.

Tracheal sounds (TS) may also be used for respiratory diagnosis and may be especially valuable to detect apnea. Tracheal sounds originate from the vibrations of the tracheal wall and surrounding soft tissues caused by gas pressure fluctuations in the trachea [15]. Undetected apnea can lead to severe hypoxia, bradycardia, and even cardiac arrest. The signals from a microphone placed over the trachea have been processed to monitor respiratory rate and to estimate respiratory flow in awake subject [16–18], and to diagnose sleep apnea–hypopnea syndrome during normal sleep [19, 20]. Yu et al. [21] found that the entropy of the acoustic signal from a microphone placed over the trachea may reliably provide an early warning of the onset of obstructive and central apnea in volunteers under sedation. In another research, Ahlstrom et al. [22] investigate the stationarity, linearity and chaotic dynamics of respiratory sound using both LS and TS to separate health and disease subjects.

According to the World Health Organization [23], heart diseases remain major killers. Thus, using a modern information processing scheme to diagnose heart disease is vital. Nowadays, methods for the diagnosis of heart disease include non-invasive techniques (ECG, chest X-rays, heart sound analysis and ultrasound imaging) and invasive techniques (e.g., angiography). Of these methods, heart sound (HS) analysis is a noninvasive, economical, easy and efficient method widely used to diagnose heart disease and evaluate heart functions during medical evaluations of adults and children [24].

Recorded lung sound signals contain noise from several sources, such as heart sounds, friction rubs, and the surrounding environment. The latter sounds can be reduced with careful microphone placement and by using soundproof rooms, but HS noise is unavoidable [25]. As we show later, HS and LS have overlapping frequency spectra, and even though filtering is often employed to reduce HS, this results in loss of important signal information. Thus recording HS can be useful for two reasons, one for using in the diagnosis of heart disease and other for HS removal from recorded lung sounds.

Acoustic monitoring can also be performed to the analysis of both ventilated patients and patients breathing spontaneously. There is a need for a continuous monitor of respiratory rate in spontaneously breathing patients at risk for respiratory depression [26]. Patients with obstructive sleep apnea (OSA), morbid obesity, or the elderly appear to be at higher risk for opioid-induced respiratory depression [27, 28]. Recently, Ramsay et al. [29] develop a noninvasive bioacoustic sensor for respiratory rate monitoring. They determine the accuracy and reliability of this bioacoustic sensor technology for the measurement of respiratory rate and detection of apneas in adult postsurgical patients as compared with the use of side-stream capnometry, as well as with a reference standard. These signals can also be used for breathing phase monitoring [3].

In this study, we developed a prototype acoustic respiratory monitoring consisting of a series of microphones of various designs, a custom-built six-channel amplification system, a USB-based data acquisition system, and the ability to display information in the time-domain and the frequency-domain. The system is be able to record heart sounds, tracheal sounds, left and right lung sounds and ventilator sounds in both the inspiratory and expiratory circuits, simultaneously. We hypothesized that the system might be helpful to the anesthesiologist and other clinicians in recognizing clinical conditions such as wheezing, bronchospasm, endobronchial intubation, and apnea.

2 Methods

We collected the heart sounds from adults at the ICU of Mehr Hospital in Tehran between 2013 and 2014. Data were collected from a total of 45 cases with an age range of 43–80 years. Written informed consent was obtained; copies are available for review by the Editor-in-Chief of this journal. The data were recorded using a laptop computer-based recording system developed at the Science and

Research Branch of Islamic Azad University. Figure 1 shows the system. A miniature electret microphone, connected to a precordial chest piece, is connected to a commercial audio amplifier whose output is then digitized at 44 kHz with 16 bits resolution. The amplified microphone signals are connected to a USB-based data acquisition module. In order to achieve high-quality recordings free of environmental artifacts, the clinical recording environment was kept completely silent. Each recording lasted 2 min. We used MATLAB in conjunction with its signal processing and real-time data acquisition toolboxes as the computational heart of the system. In order to reduce the effect of ambient noise and heart sounds, we have used wavelet transform methods to separate the respiratory sounds from the other sounds. All sounds were recorded using the software, which includes tools for recording, playing, filtering, and analyzing sounds; Fig. 2 shows the schematic of the recording process. In all cases, the operator recorded the acoustic signals using left and right midclavicular microphones as well as a microphone located in the sternal notch. Two more microphones were located over the trachea and over heart where the loudest amplitude signal was found. Two additional microphones were located on the inspiratory and expiratory ventilator

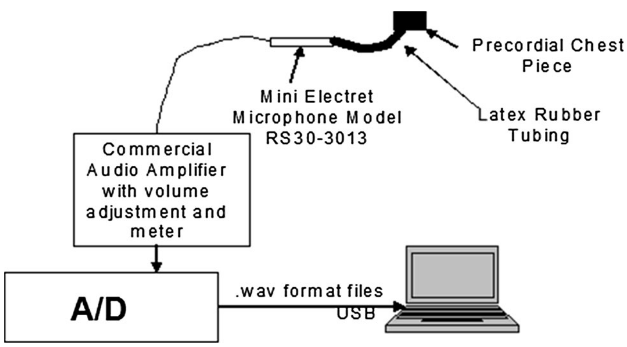


Fig. 1 The recording system details

Fig. 2 The schematic of recording system

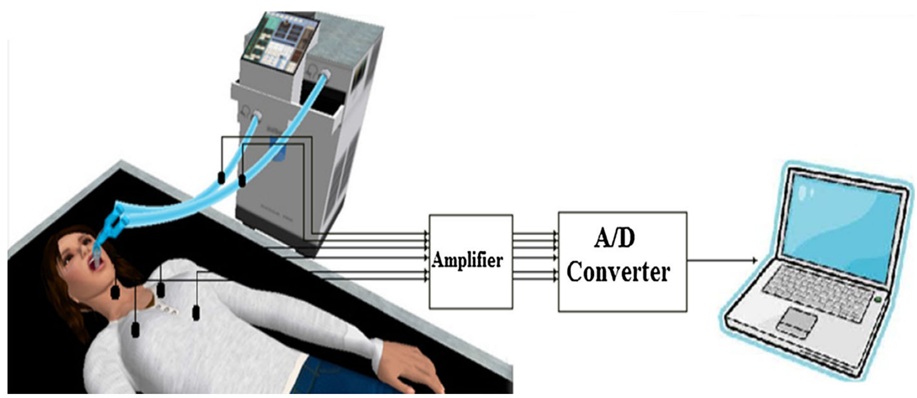
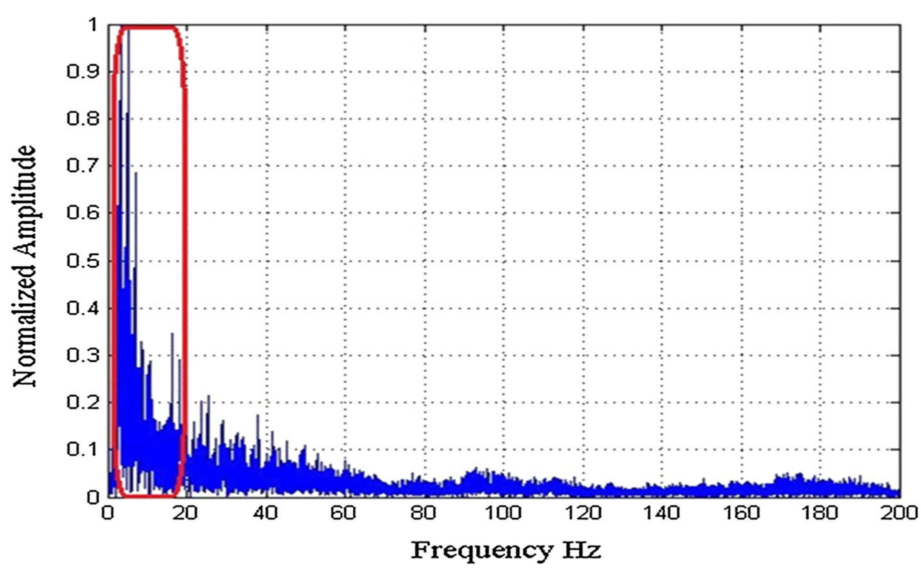


Fig. 3 The discrete Fourier transform of a sample from right lung



circuits; these microphones were sterilized before being used in the system.

During recording, the frequency was set on 1 kHz and the recorded sound was normalized in the domain of [−1, +1]. We chose this frequency to enable us to record the sounds in much time. If we chose 2 kHz frequency, then we would not able the sounds for more than 15 s due to limitation of our system. However, the frequency of 1 kHz could be enough for recording most vital sounds like heart and respiratory system. The discrete Fourier transform of a sample from right lung is shown in Fig. 3. One challenging problem we encountered was the effect of ventilator's sound on the microphone placed over the heart. To deal with this, we used wavelet transforms [31] to find this noise signal and delete it from the recorded sound. Another problem encountered were environmental noises; these noises were found in all recorded sounds of six microphones. While was possible to delete the noises using high pass filter (HPF) or wavelet but we preferred to use wavelet because HPF could harm the raw signals. Figure 4 represents the right lung signal after using wavelet methods. We believe that the recorded sounds from the right lung might be the best signal for respiratory system studies. The reason is that right lung is farther from the heart and the heart beat affects the respiratory sound less. Figure 5 shows the right respiratory sound of right lung after deleting all low frequency noises. The oscillations relate to inhale and exhale. Figure 6 shows the separated heart signal, the first and second heart sounds can be seen in the graph. Finally, we

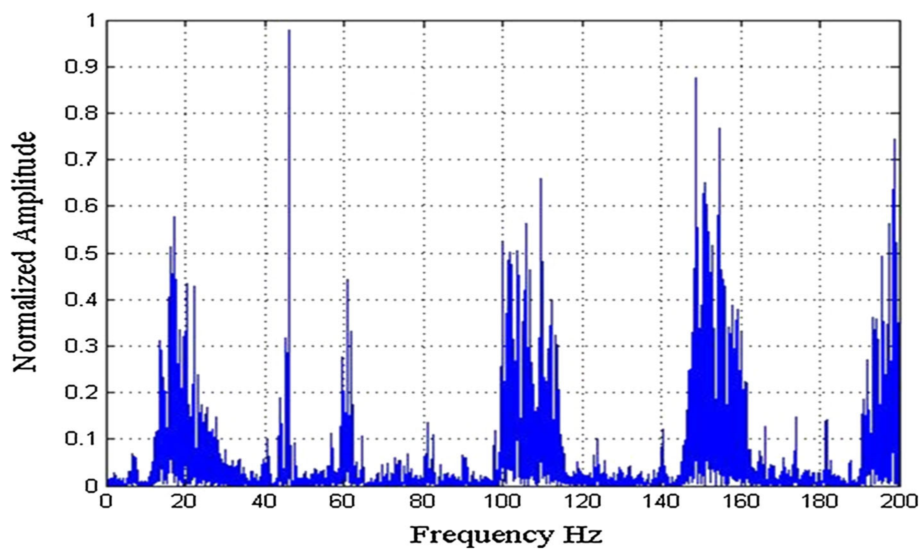


Fig. 4 The right lung signal after using wavelet methods

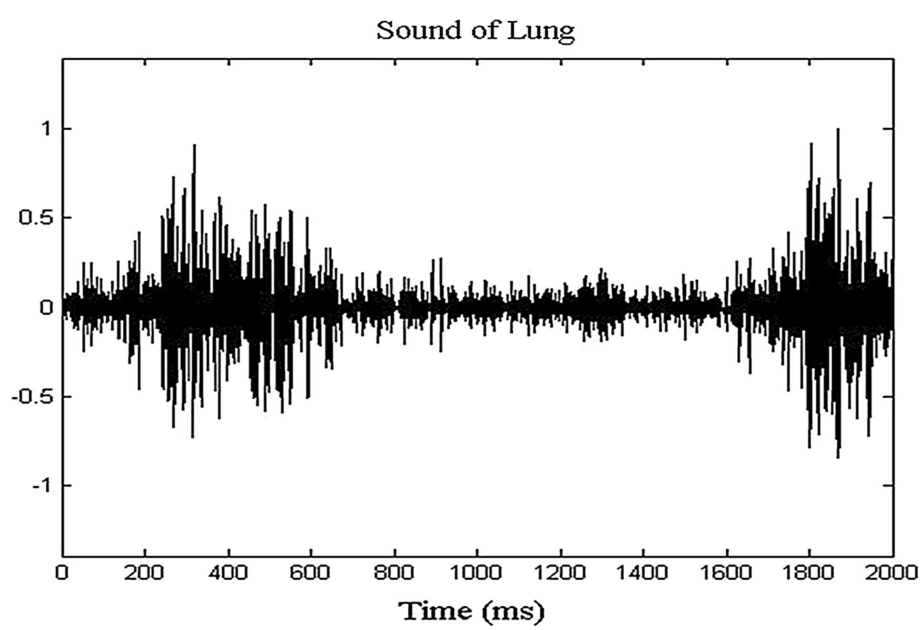


Fig. 5 The right respiratory sound of right lung after deleting all low frequency noises

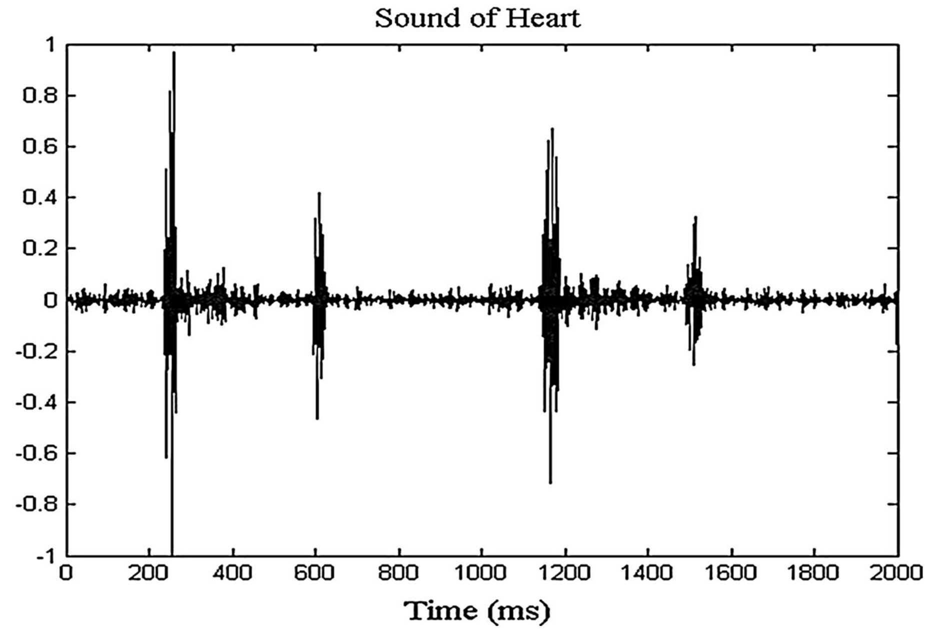


Fig. 6 The separated heart signal, the first and second heart sounds

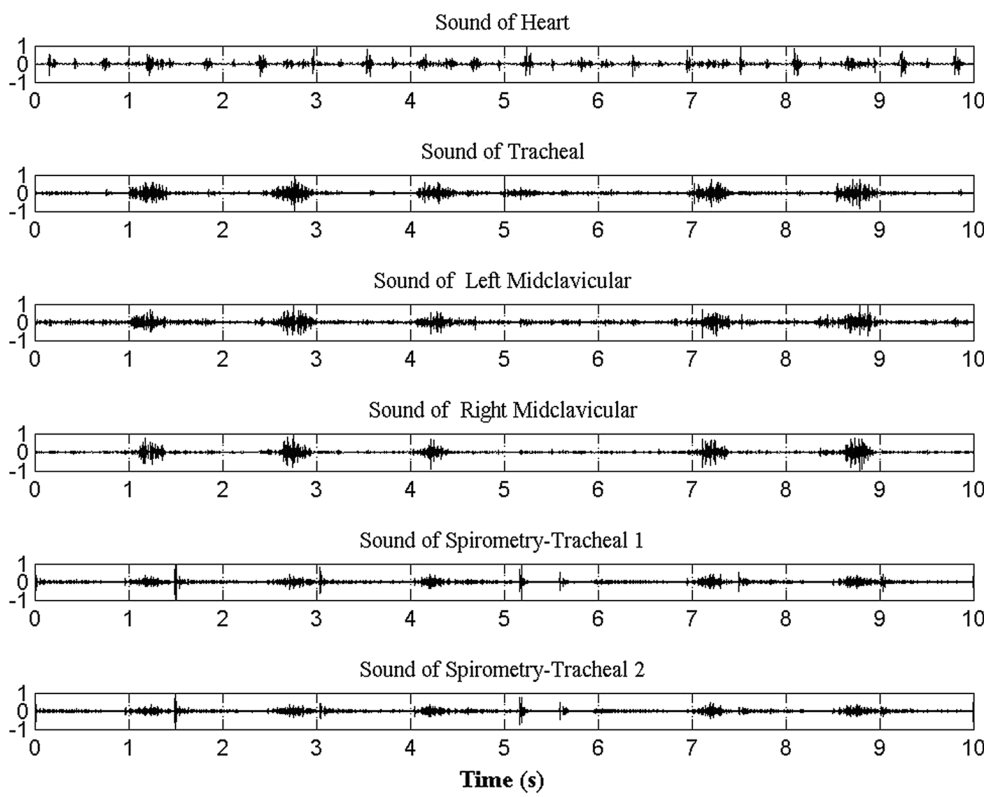


Fig. 7 The recorded sounds of six microphones for 10 s

performed a pre-processing operation and showed the recorded sounds of six microphones for 10 s in Fig. 7. As it can be seen, the sounds obtained from the inspiratory and expiratory ventilation limbs are similar.

3 Results

The results of the recording for ten cases are shown as follows. The cases' details are provided in Table 1.

Table 1 The detail of recorded cases

Case no.	Sex	Consciousness condition	Age	Disease
1	M	Conscious	64	Renal
2	M	Unconscious	67	Heart
3	F	Conscious	73	Heart
4	F	Unconscious	71	Heart
5	F	Conscious	58	Accident
6	M	Unconscious	83	Heart
7	F	Unconscious	69	Heart
8	F	Conscious	52	Renal
9	M	Unconscious	59	Lung
10	F	Unconscious	64	Heart

Case 1 Figure 7 depicts the sounds of heart, tracheal, left midclavicular, right midclavicular, ventilator inlet/outlet sounds for a 64 year old man.

Case 2 Figure 8 shows the recorded sound of heart and respiratory system for a 67 year old man.

Case 3 Figure 9 shows the data for a 73 year old woman.

Case 4 Figure 10 belongs to the respiratory data of a 71 year old woman.

Case 5 Figure 11 depicts the data for a 58 year old woman.

Case 6 Figure 12 shows the recorded sounds of an 83 year old man.

Case 7 Figure 13 represents the sound data for a 69 year woman.

Case 8 Figure 14 represents the sound data for a 52 year woman.

Case 9 Figure 15 represents the sound data for a 59 year man.

Case 10 Figure 16 represents the sound data for a 64 year woman.

4 Discussion

In this study, we aimed to introduce a new monitoring method for the analysis of respiratory sounds aimed at ultimately helping anesthesiologists and other clinicians to recognize clinical conditions such as apnea. We tried to compare our results with previous investigators but found only one similar paper. Zhang et al. [32] separated the heart sounds from the lung and showed the obtained signals. The

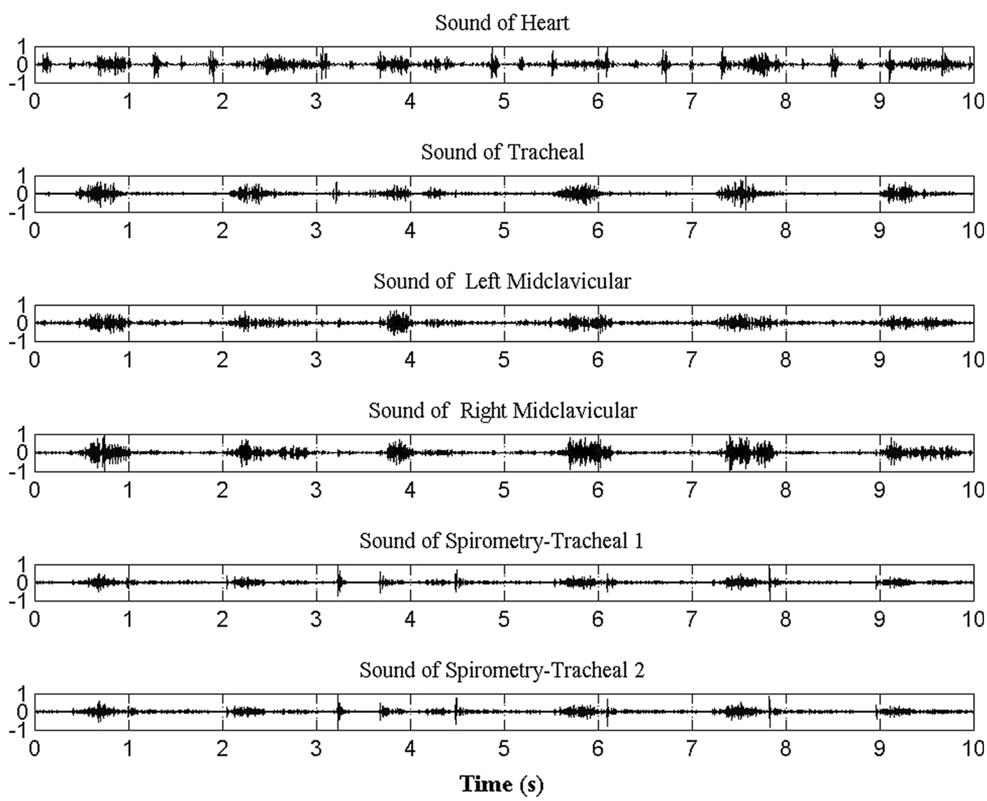


Fig. 8 The recorded sound of heart and respiratory system for a 67 year old man

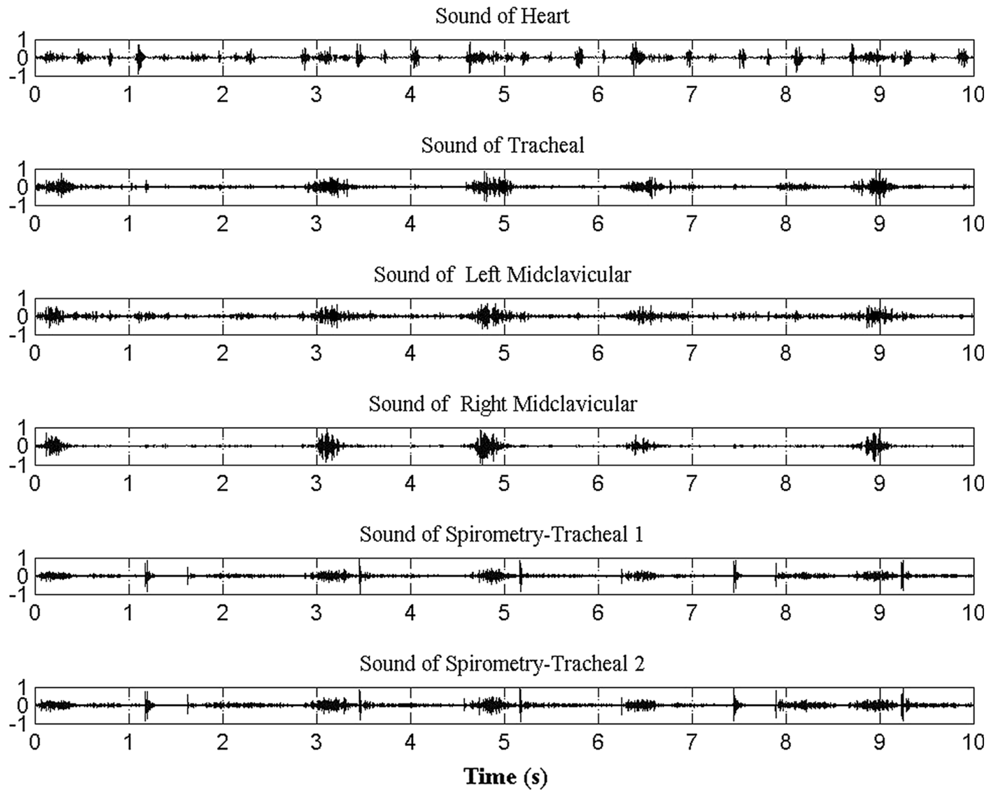


Fig. 9 The data for a 73 year old woman

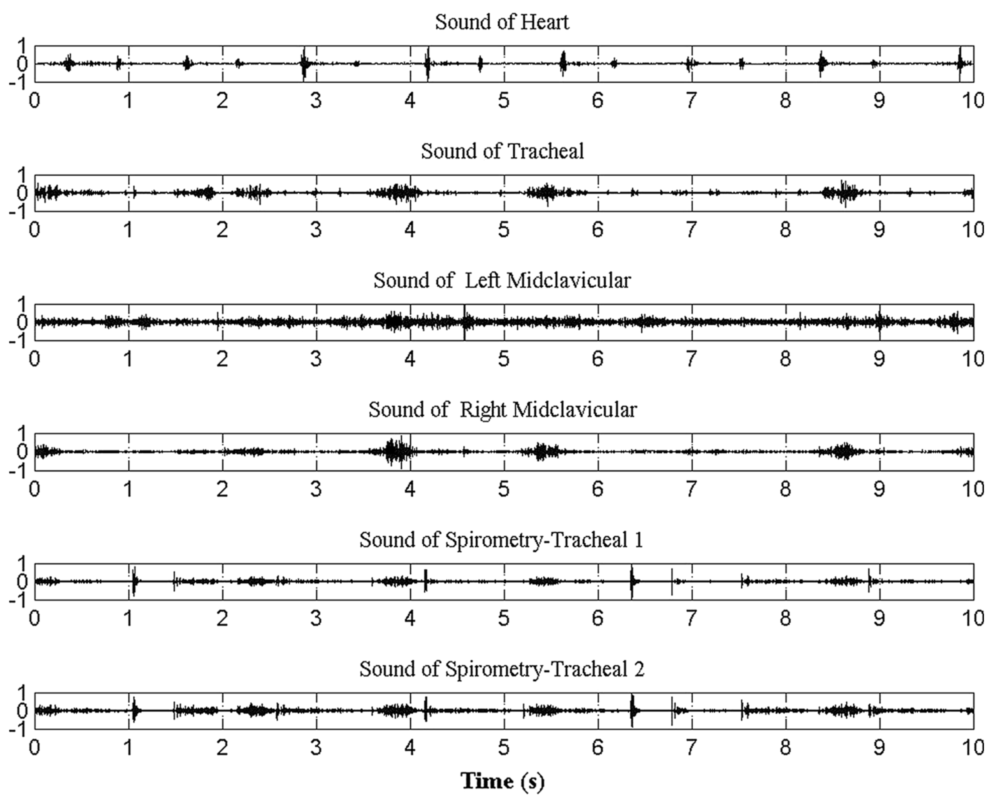


Fig. 10 The respiratory data of a 71 year old woman

Fig. 11 The data for a 58 year old woman

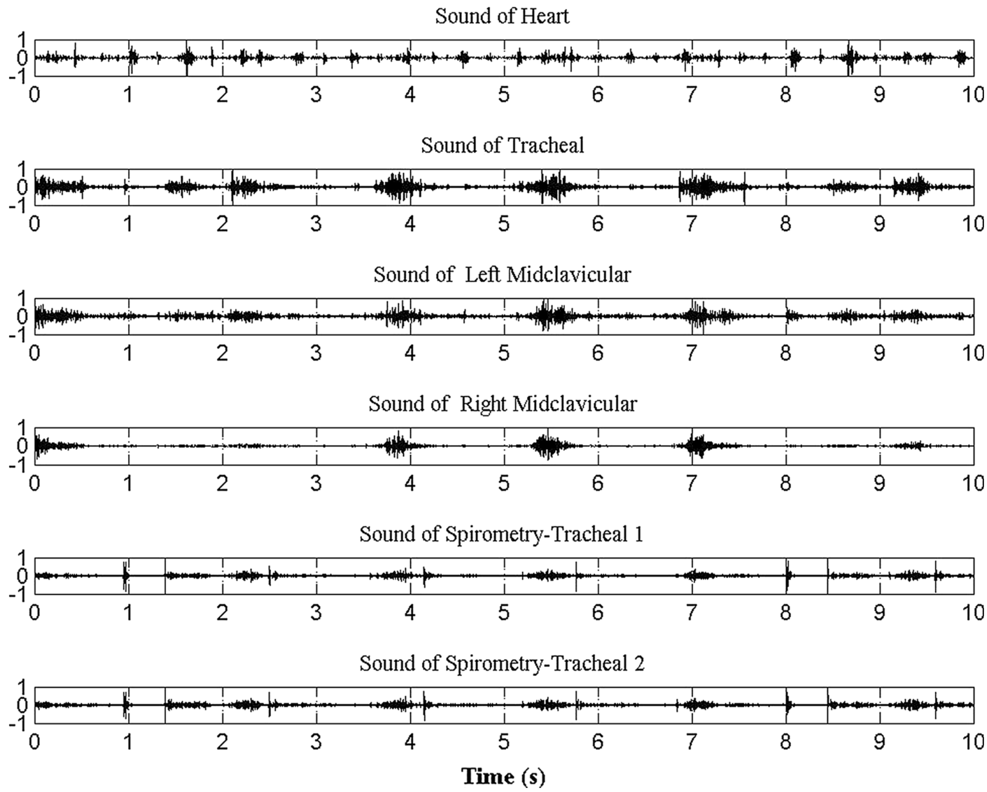
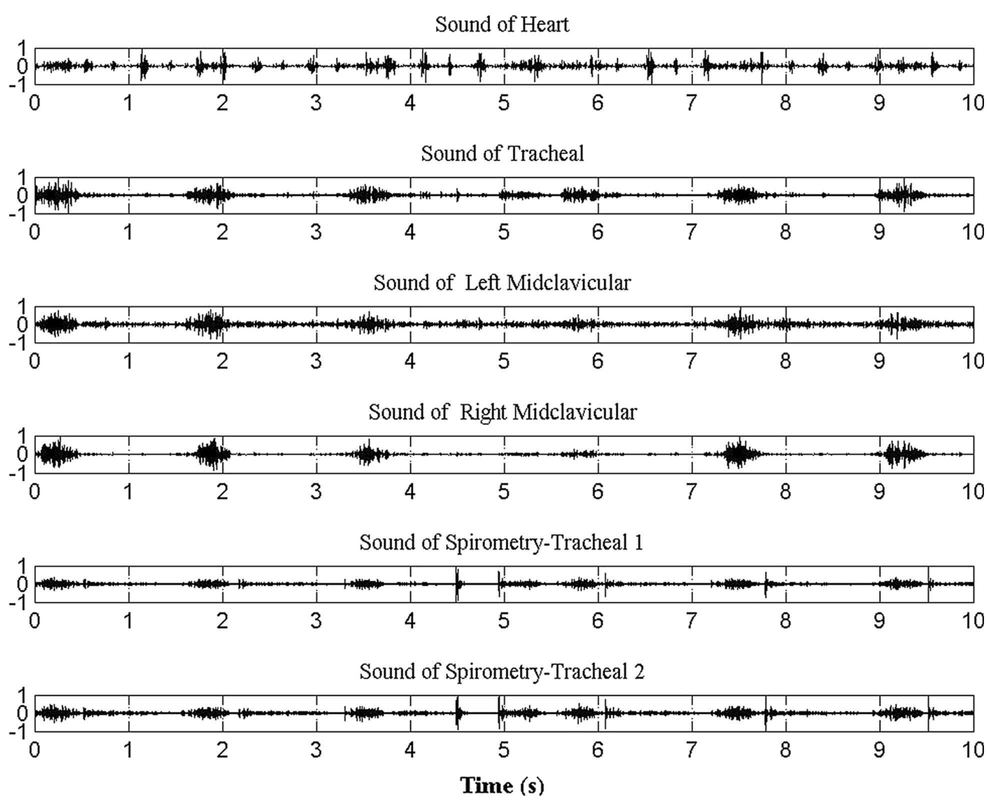


Fig. 12 The recorded sounds of an 83 year old man



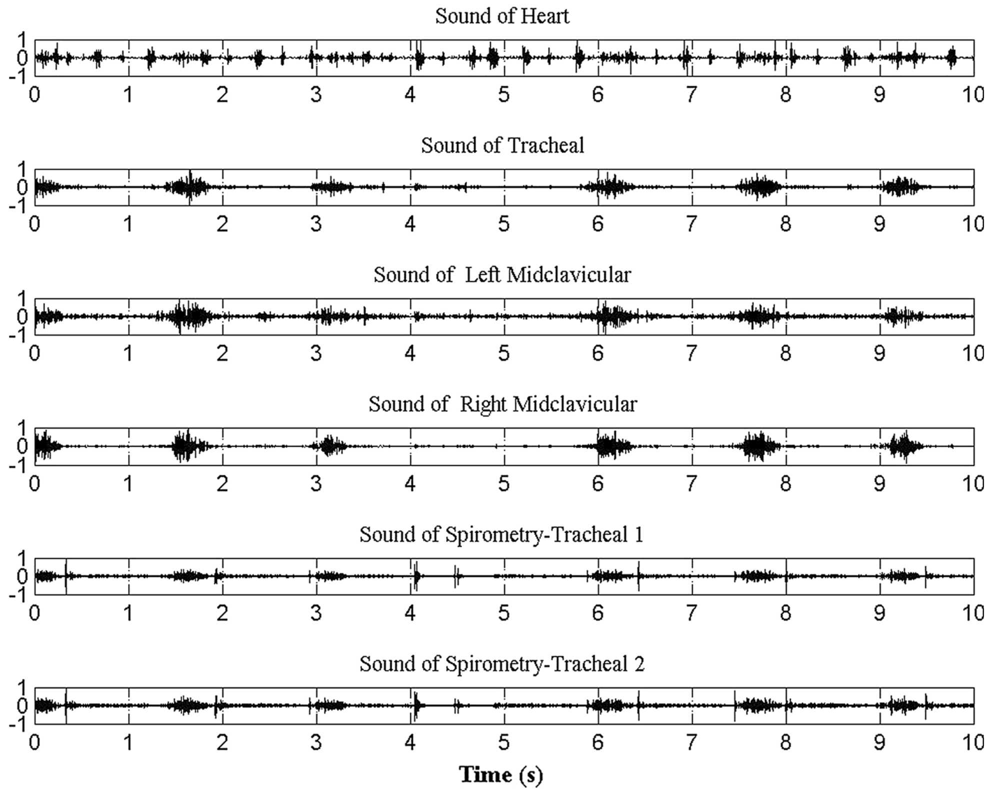


Fig. 13 The sound data for a 69 year woman

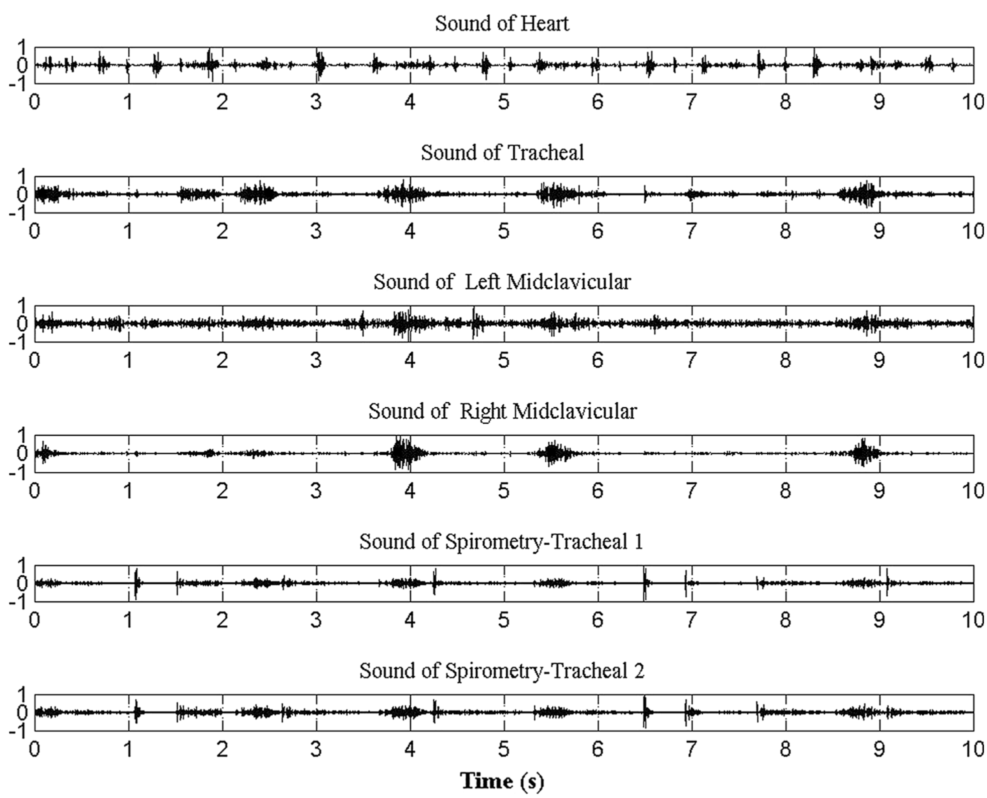


Fig. 14 The sound data for a 52 year woman

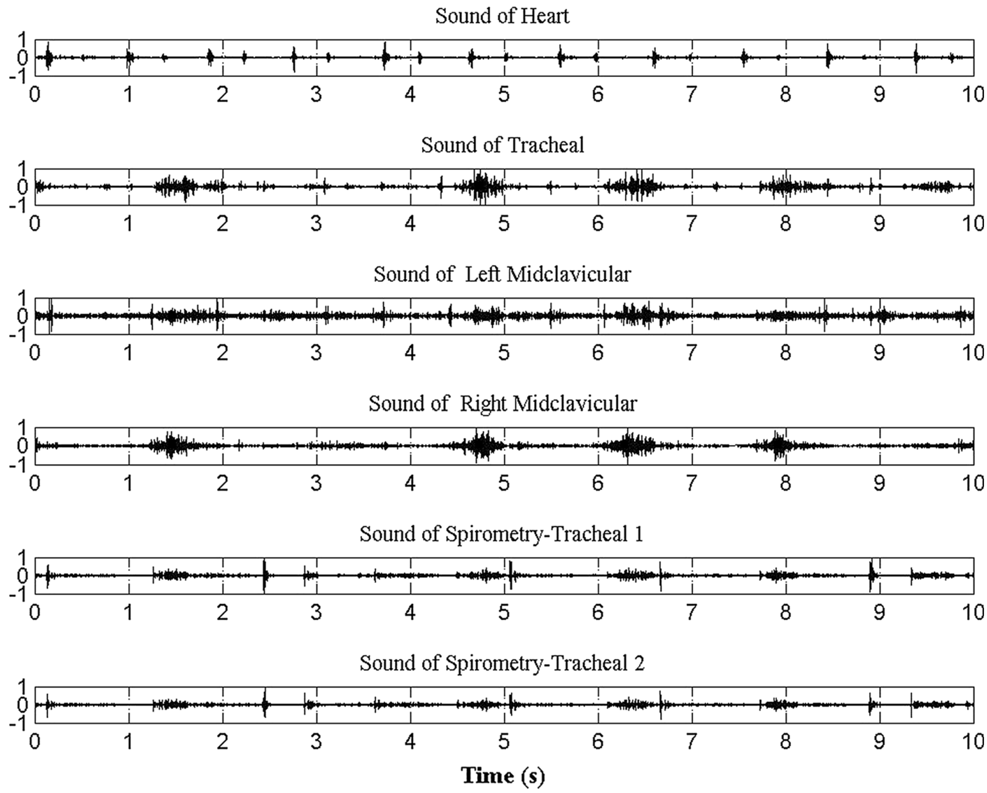


Fig. 15 The sound data for a 59 year man

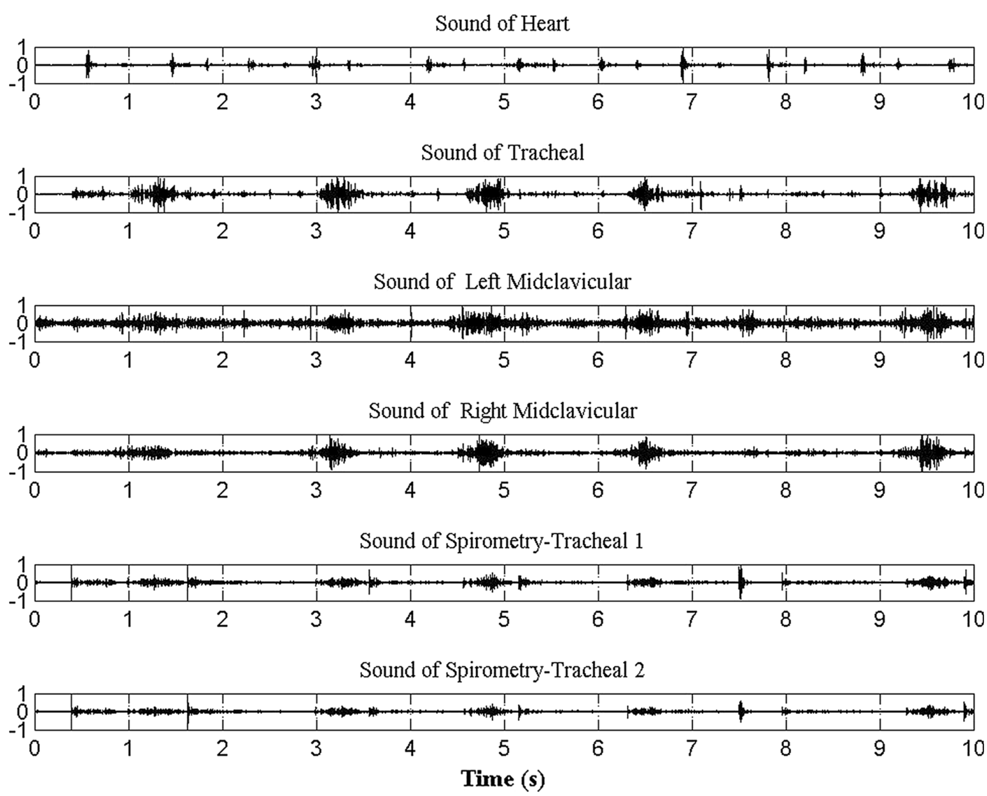


Fig. 16 The sound data for a 64 year woman

lung signal was nearly the same as our Fig. 5 but they have not omitted the noise from the lung sounds.

We expect that with refinement our prototype system will be useful for a number of clinical purposes. For example, under apneic conditions there are no breath sounds, so the signals obtained during apneic periods would be expected to reflect background noise conditions. With endobronchial intubation one lung is ventilated far more than the other; this difference should be readily apparent in the two (frequency-domain) color spectrograms [30] or with the use of (time-domain) X–Y plotting methods [33]. With bronchospasm or wheezing new high-frequency sounds of a quasi-musical nature should be apparent in the resulting color spectrogram [30]. However, an important limitation of this study is that we have not performed formal clinical trials to evaluate the performance of our system under these various clinical conditions. Instead, our focus was on technology development, involving the evaluation of various types of microphone designs used to record breath sounds and various band-pass filtering protocols using MATLAB. The end result has been a collection of recordings made to establish what typical respiratory acoustic signals look like.

5 Conclusion

We developed a prototype six-channel acoustic cardiopulmonary monitoring system for use in perioperative patient monitoring The system, which displays both time domain and frequency domain information is expected to be helpful in recognizing respiratory conditions like wheezing, bronchospasm, endobronchial intubation, and apnea. To date the system has provided a collection of typical respiratory acoustic signals for typical ventilated patients, with plans to collect additional acoustic data reflecting various pathological states.

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

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