Critical Reviews™ in Biomedical Engineering, 46(1):33–52 (2018)

Lung and Heart Sounds Analysis: State-of-the-Art and Future Trends

A.L. Padilla-Ortiz[a,b,*] & David Ibarra[c,d]

[a]CONACyT-CICESE, Unidad Monterrey, Alianza Centro 504, PIIT Apodaca, 66629, México; [b]ITESM Campus Ciudad de México, Calle del Puente 222, Col. Ejidos de Huipulco, Ciudad de México 14380, México; [c]Tecnológico de Monterrey, Escuela de Ingeniería y Ciencias, Av. Eugenio Garza Sada 2501 Sur, Col. Tecnológico, C.P. 64849 Monterrey, Nuevo León, México; [d]Massachusetts Institute of Technology, Department of Mechanical Engineering, Cambridge, MA, 02139

*Address all correspondence to: Ana Laura Padilla-Ortiz, CONACyT-CICESE, Unidad Monterrey, Alianza Centro 504, PIIT, Apodaca, Nuevo León, México; Tel.:+52 (81) 8196-0350 ext. 28415, E-mail: apadilla@cicese.mx

ABSTRACT: Lung sounds, which include all sounds that are produced during the mechanism of respiration, may be classified into normal breath sounds and adventitious sounds. Normal breath sounds occur when no respiratory problems exist, whereas adventitious lung sounds (wheeze, rhonchi, crackle, etc.) are usually associated with certain pulmonary pathologies. Heart and lung sounds that are heard using a stethoscope are the result of mechanical interactions that indicate operation of cardiac and respiratory systems, respectively. In this article, we review the research conducted during the last six years on lung and heart sounds, instrumentation and data sources (sensors and databases), technological advances, and perspectives in processing and data analysis. Our review suggests that chronic obstructive pulmonary disease (COPD) and asthma are the most common respiratory diseases reported on in the literature; related diseases that are less analyzed include chronic bronchitis, idiopathic pulmonary fibrosis, congestive heart failure, and parenchymal pathology. Some new findings regarding the methodologies associated with advances in the electronic stethoscope have been presented for the auscultatory heart sound signaling process, including analysis and clarification of resulting sounds to create a diagnosis based on a quantifiable medical assessment. The availability of automatic interpretation of high precision of heart and lung sounds opens interesting possibilities for cardiovascular diagnosis as well as potential for intelligent diagnosis of heart and lung diseases.

KEY WORDS: review, state of the art, lung sounds, heart sounds, respiratory sound analysis, heart sound analysis

ABBREVIATIONS: CHD, coronary heart disease; **COPD**, chronic obstructive pulmonary disease; **MS**, mitral stenosis; **MVP**, mitral valve prolapse; **PS**, pulmonary stenosis; **TB**, tuberculosis; **VAS**, valvular aortic stenosis; **WHO**, World Health Organization

I. INTRODUCTION

A recent study identifies cardiovascular disease (17.9 million), cancer (8.8 million), and chronic respiratory diseases (3.8 million) as the major causes of death from noncommunicable diseases in 2015.[1] Chronic obstructive pulmonary disease (COPD), asthma, acute respiratory infections, tuberculosis (TB), and lung cancer are the most common respiratory diseases to result in severe illness and death worldwide.[1]

The World Health Organization (WHO) reports that an estimated 6% of all deaths worldwide (more than 3 million people) occur each year from COPD.[2] COPD is currently the fourth leading cause of death in the world,[3] but it is projected to become the third leading cause of death by 2020.[4] Approximately 235 million people currently suffer from asthma. The most common chronic disease of childhood,[5] asthma affects 14% of children globally, and that number is on the rise.[6] More than 4 million people die of respiratory infections every year.[7] For many years, acute lower respiratory tract infections (pneumonia and acute bronchitis) have been among the top three causes of death and disability among both children and adults.[7] It has been reported that 10.4 million people fell ill with TB, with an estimated 1.4 million deaths from TB occurring in 2015.[8] Lung cancer is the most common cause of cancer-related deaths worldwide (1.69 million people annually).[7]

Approximately one in every four deaths (700,000) annually in North America are the result of heart disease.[9] In the United States, heart disease is the leading cause of death in both men and women, but more than half of heart disease deaths in 2009 occurred in men. Coronary heart disease (CHD) is the most common type of heart disease, resulting in more than 400,000 deaths annually in North America. Every year, ~800,000 Americans suffer a heart attack. Of these, 550,000 have their first heart attack, and 250,000 have already had at least one.[10]

Someone diagnosed with heart disease has a poor prognosis.[11] Its presence commonly signals the final phase of many processes, and one of the most noticeable is ischemic heart disease. Mortality associated with heart disease is comparable to that due to common cancers, with a survival rate of < 49% during a span of 4 yr.[12] Despite this data, current technology in treatment has brought improved quality of life and survival to heart-failure patients. On the other hand, improved survival and the many comorbidities[13] are accompanied by additional health problems. Recent studies show that a substantial number of heart-failure patients die from causes other than the cardiac disease, in particular, events due to malignancies, respiratory problems, and septicemias.[14]

II. LUNG AND HEART SOUND CHARACTERISTICS

A. Lung Sounds

The respiratory cycle has two stages. During the inspiration phase, the oxygen-rich air flows into the lungs so that the chest cavity, including the lungs, expands. Intercostal muscles (muscles attached to the chest) and the diaphragm contract in a downward direction. Conversely, during the expiration phase, air is forced out so that the chest relaxes, the volume of the chest cavity decreases, the lungs are forced to compress, and the intercostal muscles and diaphragm relax. Carbon dioxide-rich air (CO_2) is expelled during the expiration phase.[15]

Respiratory sounds are produced by airflow within the chest cavity. Characteristics of normal breath sounds are shown in Figs. 1 and 2.[16] When the airflow within the chest is interrupted by a pulmonary deficiency, the sounds generated have certain specific characteristics (see Figs. 3 and 4). The information contained within the signal waveform such as frequency, intensity, and timbre (or quality) are characteristics of respiratory sounds that can help to diagnose common pulmonary diseases.[17,18]

B. Heart Sounds

Some of the common mechanisms by which heart sounds are generated include (1) opening or closing heart valves, (2) flow of blood through the valve orifice, (3) flow of blood into the ventricular chambers, and (4) rubbing of cardiac surfaces.[19] These mechanisms produce four principal heart sounds (shown in Fig. 5) that consist of the following:

- Vibrations generated by closure of the mitral (M1) and tricuspid (T1) valves produce the first heart sound (S1). This corresponds to the end of diastole and beginning of the ventricular systole and precedes the upstroke of carotid pulsation.[20]
- The second heart sound (S2) is produced by the closure of the aortic (A2) and the pulmonary (P2) valves at the end of systole. Intensity depends on valvular factors, transvalvular gradient, mechanical factors, and size of the great vessels.[21]
- The third heart sound (S3) is a low-pitched, early diastolic sound, audible during the rapid entry of blood from the atrium to the ventricle. S3 occurs when rapidly rushing blood from the atria is suddenly decelerated by the ventricle when it reaches its elastic limit. In a normal ventricle, this can happen with an excessive volume of incoming blood or in hyperdynamic states or volume-loaded conditions.[22]
- The fourth heart sound (S4) is a late diastolic sound that corresponds to late ventricular filling through active atrial contraction. Ventricular theory proposes that S4 is generated by sudden deceleration of the jet of blood as it enters a ventricle with decreased compliance. Impact theory proposes that S4

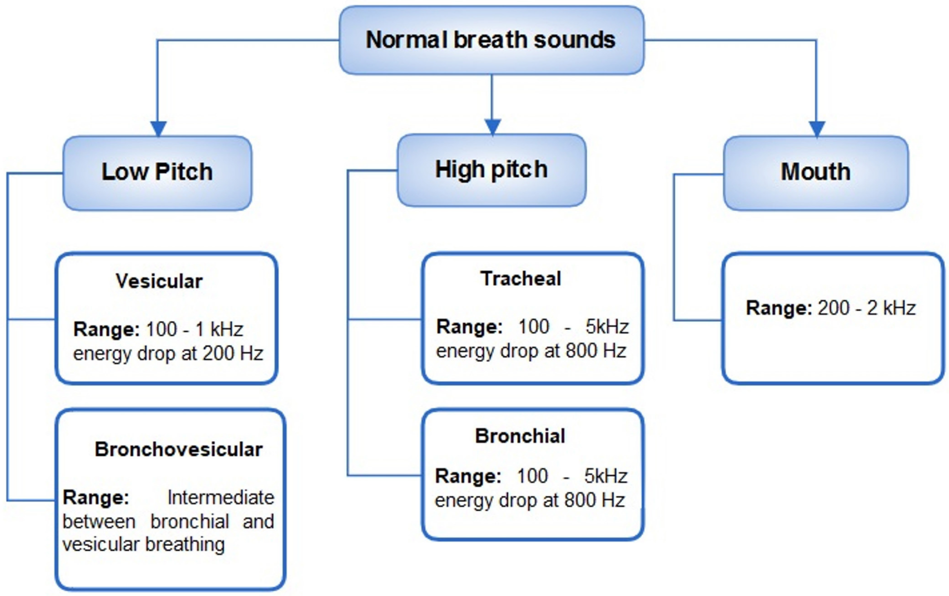

FIG. 1: Characteristics of normal breath sounds

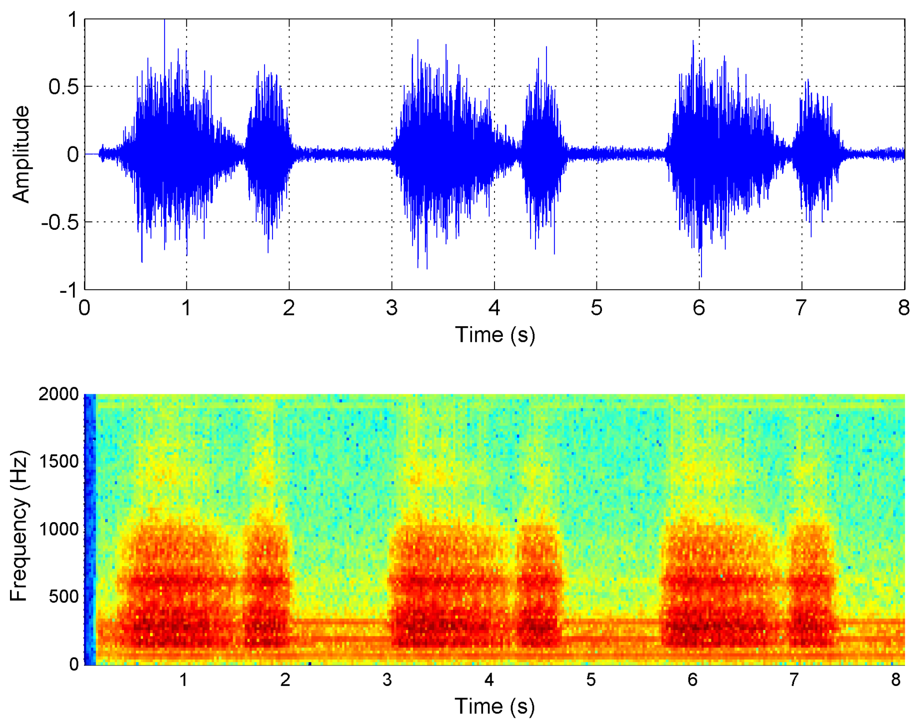

FIG. 2: Time-domain characteristics (top) and spectrogram (bottom) of normal breath sounds

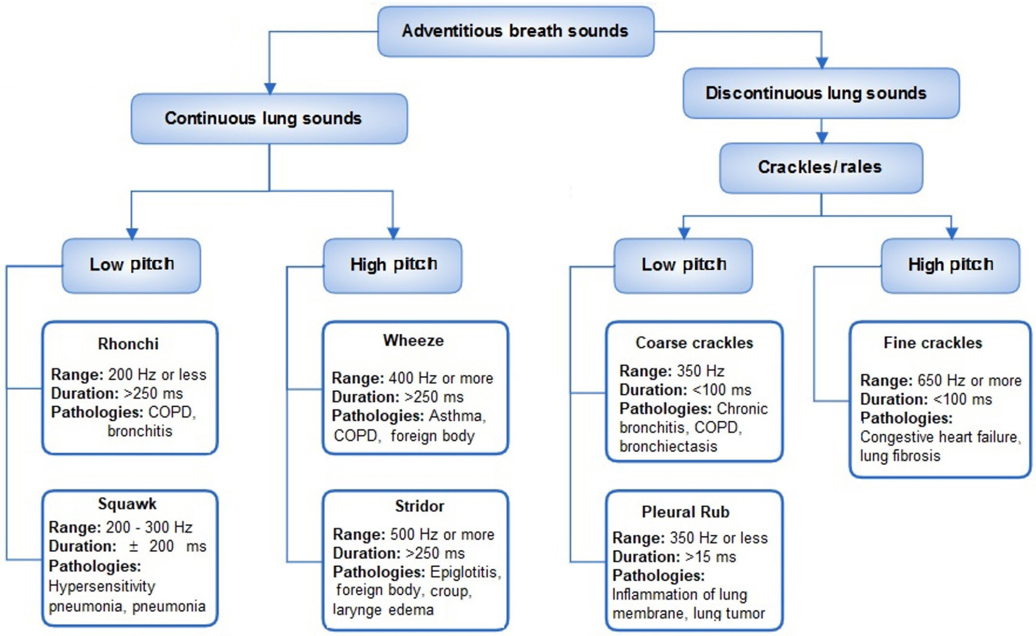

FIG. 3: Types and characteristics of adventitious sounds, based on Palaniappan et al.[16]

is the result of the movement and impact of the blood on the ventricle following atrial expulsion. Active atrial contraction is necessary for the generation of S4.[23]

Several studies[24–26] have shown that for both S1 and S2 the major concentration of energy is below 150 Hz, which may indicate that both sounds are caused by vibrations within the same structure, possibly the entire heart. However, S2 spectra have greater amplitude than S1 spectra, above 150 Hz, which may be due to vibrations within the aorta and pulmonary artery.[27] Heart sound classification is presented in Fig. 6, and its magnitude spectrogram is shown in Fig. 7.

C. Auscultation

Auscultation is a rapid, relatively easy, effective, and noninvasive technique often used by trained physicians to diagnose respiratory and cardiac diseases.[28] Auscultation usually is performed with a stethoscope, an acoustic medical instrument invented by Laennec in 1816.[29] Initially, a rolled paper cone, considered to be the first stethoscope, was succeeded by a hollow tube of wood.[30] Due to the high number of modifications to the original model, the modern stethoscope is much different from the first model. More recent stethoscopes can record and send the recorded sounds to a personal computer for processing and analysis.[31] Auscultation with a stethoscope is a highly subjective process and depends on several factors including experience and skill of healthcare professionals and their ability to recognize different sound patterns.[32] For respiratory examination, additional requirements must be considered. For example, the patient must be seated and auscultation performed in a quiet room to reduce ambient noise.[17]

Research conducted by Abella et al.[33] showed that amplification at low frequencies in stethoscopes occurs below 112 Hz, the point at which heart sounds can be heard;[27] however, in this range, the human ear loses sensitivity.[34] This represents a major problem for diagnosis.

Such disadvantages regarding auscultation have been overcome by means of computerized analysis of recorded lung and heart sounds.[32] Computerized analysis enables a systematic approach to the diagnosis of different respiratory or cardiac diseases.[35] Computerized lung and heart

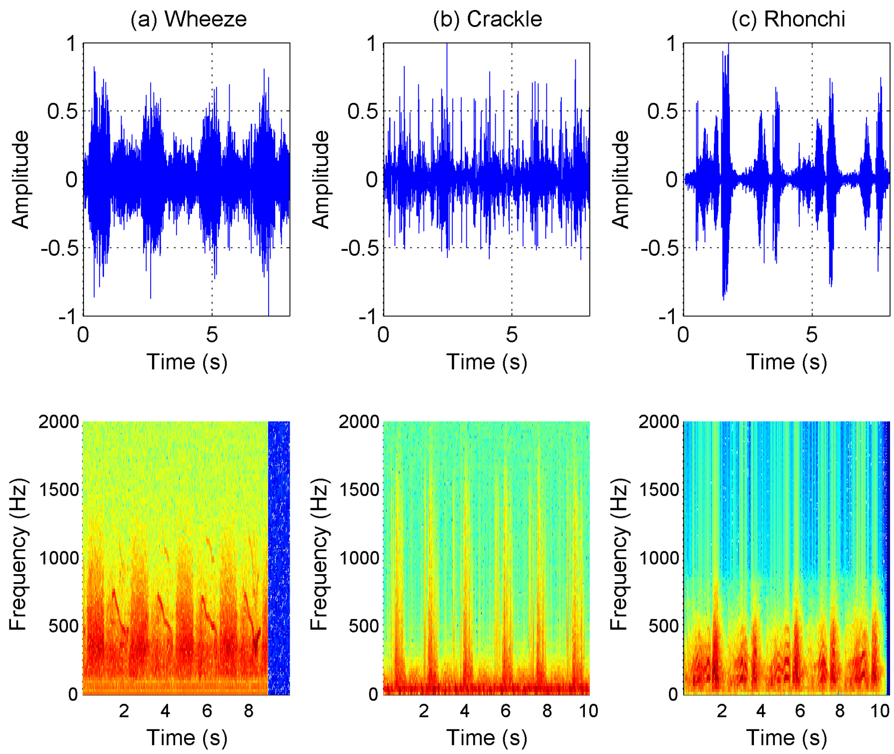

FIG. 4: Adventitious lung sounds (ALS) waveforms (top) and spectrogram (bottom) of (a) wheeze, (b) crackle, and (c) rhonchi

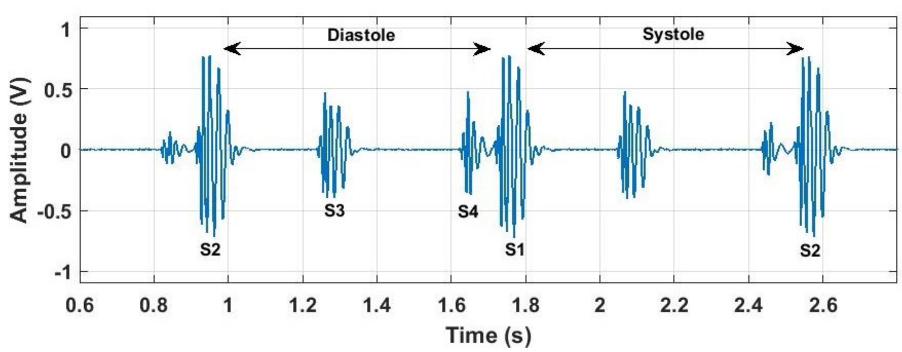

FIG. 5: Heart sound waveforms

sound analysis takes place in different stages. (1) Acoustic signals generated by the human body are acquired and recorded by an electronic device. (2) At the feature extraction stage, the most relevant information is culled from a large set of measurements. (3) The final stage is classification, which recognize the feature class based on the properties of the features selected from previous stage.[35]

III. OVERVIEW OF SOUND DATABASES

A. Lung and Heart Sound Databases

Lung and heart sound databases[36,37] have been developed as learning tools and enhance problem-solving skills in the area of respiratory medicine. In many cases, clinical data are recorded at considerable

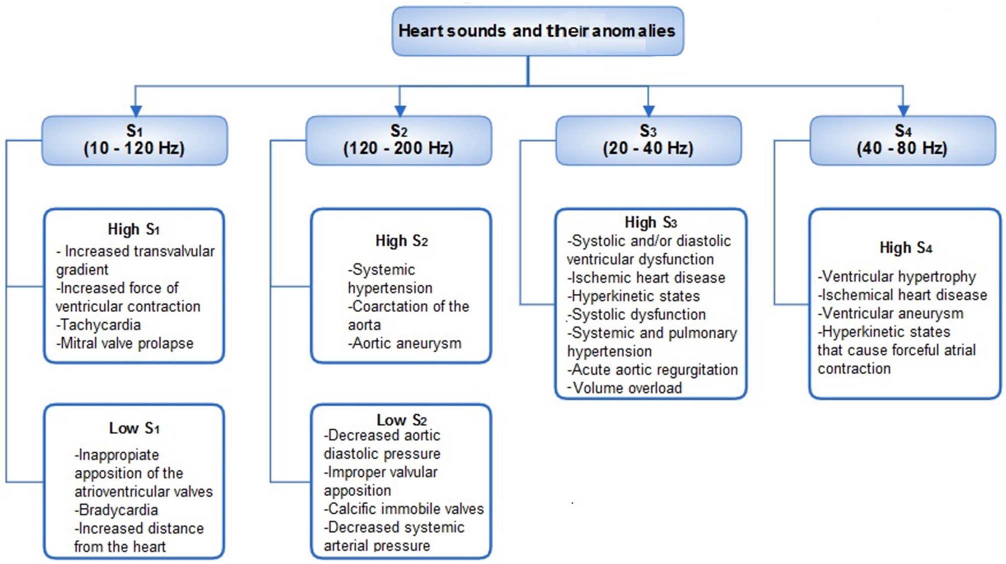

FIG. 6: Types of heart sounds and their characteristics

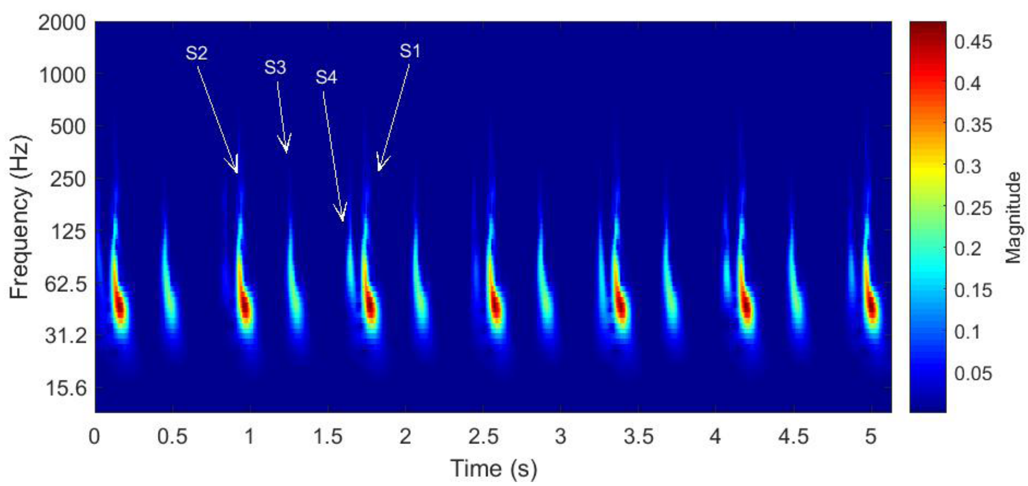

FIG. 7: Magnitude spectrogram of heart sounds

expense, used for diagnosis once, and then filed away indefinitely. Moreover, the effort needed to document data for storage and sharing in a semipermanent manner is rarely available at the close of a research project. Some of the most relevant databases are described below.

1. Lung Sound Databases

- Marburg Respiratory Sounds (MARS) is a database of respiratory sounds measured in actual patients. MARS database has stored more than 5000 sound recordings from patients with different diseases, including bronchial asthma (50 patients), COPD (40), lung fibrosis (5), and pneumonia (45), as well as healthy individuals (250). Clinical parameters such as lung function, laboratory results, and X-ray findings are included. Three independent pulmonary experts have evaluated and confirmed these lung sound recordings.[36]

- The Respiratory Acoustics Laboratory Environment (RALE) repository, often used by researchers, is a computer-aided instruction program on chest auscultation. It includes a respiratory sound database with examples of several lung sounds, sonograms, and quizzes. Unlike MARS, RALE is not open-source software.[37]

In addition to these lung sound databases, open-source applications are available, and some are described below:

- The Physiological Signal Analysis System (PhiSAS) was developed for the observation of lung sounds and provides an objective analysis. PhiSAS allows sound recording and is equipped with a wide range of processing and analysis tools including Fourier, wavelet, and time-frequency analysis.[38]
- LungSounds@UA is an interface developed in Matrix Laboratory (MATLAB) to collect and organize respiratory data in a single multimedia database. It is possible to record respiratory sounds in these seven, most relevant locations: trachea, anterior left and right, lateral left and right, and posterior left and right areas of the chest.[39]
- Respiratory Sound Annotation Software (RSAS) was developed in MATLAB. RSAS is a tool used to collect lung sound reference annotations. RSAS allows sound recording,[40] and the annotation process allows health professionals to diagnose, monitor, and detect cardiorespiratory disease through the use of adventitious lung sounds (ALS) such as crackles, wheezes, and phase-on respiratory sounds.
- Computerised Lung Auscultation—Sound Software (CLASS), developed in Java, integrates recording, annotation, and tutorials regarding respiratory sounds. This tool was assessed by physiotherapy students to identify its limitations and has been found to be useful in academic and clinical environments.[41]

2. *Heart Sound Databases*

The PhysioNet/Computing in Cardiology (CinC) Challenge of 2016[42] attempts to access the research community in an effort to contribute to multiple promising databases.[43] Such a group can generate high-quality heart sounds. Before the PhysioNet/CinC Challenge 2016, only three public, heart sound databases were available: (1) A database from the University of Michigan Heart Sound and Murmur Library (MHSDB), (2) the PASCAL database,[44] and (3) the Cardiac Auscultation of Heart Murmurs database, summarized as follows:

- The MHSDB, provided by the University of Michigan Health System, includes only 24 heart sound recordings with a total time length of 1500 s.[45]
- The PASCAL database contains 177 recordings for heart sound segmentation and 657 recordings for heart sound classification. Recordings last from 1 to 29 s but have a limited frequency range below 200 Hz, due to the applied low-pass filter that removes many of the useful heart sound components for clinical diagnosis.[44]
- The Cardiac Auscultation of Heart Murmurs database, provided by eGeneral Medical Inc., includes 65 recordings. It is not open and thus requires paid access.[46]

During the past few years, some websites containing rich educational material on lung and heart sound databases have been developed and can be used to train health-care professionals. They incorporate user manuals, listening tips, respiratory and cardiac sound recordings, waveforms, exercises for diagnosis training, and quizzes. These include Easy Auscultation Training,[47] Practical Clinical Skills,[48] 3M Littmann,[49] The Auscultation Assistant,[50] and SoundCloud.[51] In addition to the online repositories, several books and accompanying audio CDs for understanding lung sounds and heart sounds and murmurs are available.[15,52]

B. Lung Sound Analysis

Here, we focus on types of lung and heart sounds that have been analyzed specifically from 2011 to the present. As mentioned above, wheezes, crackles, stridors, and rhonchi are adventitious breath sounds that are heard over normal breath sounds. These sounds are characteristics of pathologies such as asthma, COPD, and pulmonary emphysema. A summary of the lung sound type analyzed, instrumentation, and data source (sensor type and/or database) is presented in Table 1.

A descriptive summary of normal cardiac sounds (S1 and S2), S3 and S4 as well as other cardiac pathologies such as murmurs, heart valvular disorder, pulmonary stenosis (PS), coronary artery disease, and others are shown in Table 2.

IV. DISCUSSION

This article presents a thorough review of technology associated with the acquisition, recording, storage, and signal processing of lung and heart sounds. We also include a detailed analysis of instrumentation along with data sources, databases, and websites. The existing literature on the analysis of pulmonary sounds focuses on wheezes and crackles. It is worth noting that a relatively small body of literature is concerned with rhonchi, stridor, squawks, pleural rub, and egophony analysis, which illustrates that additional research is needed.[54,58,64,67,80,83,84,87,97,102]

Although auscultation with a stethoscope has several disadvantages[141] and limitations,[32] it is the technique that is most frequently used because it is easy to use.[142,143] Nowadays, digital techniques including electronic stethoscopes and microphones are generally used to collect data for analysis.

According to the literature on lung sound analysis, the most common respiratory diseases that are studied include COPD,[53,54,65,75,79,83,86,87,94,101,105,144] asthma,[53,54,65,71,72,85,87,105,107,110,117] and pulmonary emphysema.[58,70,93,99,106,112] However, lung sounds recorded during pneumonia,[54,65,76,79,103] pulmonary fibrosis,[56,70,76] chronic bronchitis,[56] idiopathic pulmonary fibrosis,[63] congestive heart failure,[76,79] parenchymal pathology,[75,90] and interstitial lung disease[79,87,104] appear less frequently in the literature. Regarding heart sound analysis, it is observed that murmurs[26,121,126,131,132,135–137] and heart valve problems such as regurgitation[25,135] and stenosis[130,140] are the most common heart pathologies studied.

The creation of a heart sound database that is accessible to the research community has many potential benefits for different types of users. First, those who lack access to well-recorded clinical signals may use the data to develop and test algorithms. Second, accessibility has the potential to encourage researchers to develop innovative methods for approaching issues in heart sound signal analysis that may not otherwise have been tried.

Computerized lung and heart sound analysis represents a substantive advance in diagnosing, monitoring, treatment, and visualization signaling of respiratory and cardiac pathologies. However, due to a lack of published guidelines, significant differences exist among various laboratories, such as the use of different sensors to acquire signals (type, number, and position)[145] and signal-processing techniques.[32] For these reasons, it is difficult to make a comparison of the research produced by various laboratories. It is likely that the development of new technology along with suitable standards will allow the diagnosing of pathologies that are not frequently observed.

In that sense, a multinational effort is underway to develop specific guidelines for research and clinical practice in the field of respiratory sound analysis, with the intention of standardizing the procedure for recording respiratory sounds. This project is called Computerized Respiratory Sound Analysis (CORSA) and was developed by more than 20 scientists in seven European countries including Belgium, Britain, Finland, France, Germany, Italy, and The Netherlands.[32]

A. Toward Mobile Signal Acquisition

Recently, the development of mobile technology has significantly evolved and is often used by clinicians for data acquisition and diagnosis. A study by Reyes et al.[146] proposes the use of smartphones to acquire tracheal sounds. These researchers used two smartphones with different operating systems (Android and Apple iPhone operating system). The reference signal was acquired by a spirometer, and results showed a high correlation between the signal acquired with both smartphone devices and the signal acquired by spirometer. The same team also

TABLE 1: Lung sound types

Ref.	Data source		Lung sound type
	Sensor type	**Database**	
53	Electronic stethoscope		77 Polyphonic and 63 monophonic wheezes
54	Electret microphone	Real data and data from Refs. 15, 52, and 55	Wheeze, stridor
56	Electronic stethoscope	Real data and data from Refs. 15, 37, and 55	Crackle
57	Electronic stethoscope		Wheeze, crackle
58	Piezoelectric microphone, electronic stethoscope		Wheeze, crackle, rhonchi, and egophony
59		Ref. 37	Unspecified
60	Unspecified	Unspecified	Wheeze
61	Electronic stethoscope		Crackle, wheeze, and rhonchi
62		Ref. 37	Crackle, stridor, and wheeze
63	Unspecified	Unspecified	Crackle
64	Piezo film, microphone		Tracheal and vesicular breath sounds, inspiratory and expiratory stridor, and stridor
65	Electret microphone	Refs. 44–46	Continuous and discontinuous adventitious sound (unspecified)
66		ACCP teaching tape	Crackle
67		Refs. 37 and 68	Wheeze, normal, rhonchi, crackle, squawk, stridor
69	Electronic stethoscope		Wheeze, crackle
70	Pneumotachograph		Crackle
71	Unspecified	Unspecified	Wheeze
72	Piezoelectric microphone, pneumotachograph		Wheeze
73	Electret microphone		Unspecified
74	Digital stethoscope		Wheeze
75		Ref. 37	

TABLE 1: *(continued)*

76	Electret microphone, pneumotachograph		Crackle
77	Electret microphone, flowmeter		Crackle
78	Soft stethoscope		Wheeze
79	Electronic stethoscope		Crackle
80		Refs. 55, 81, and 82	Wheeze, stridor
83	Electronic stethoscope		Rhonchi, crackle
84	Electret microphone	Real data Refs. 15, 52, and 55	Wheeze, rhonchi, stridor
85	Unspecified	Unspecified	Wheeze
86		Ref. 37	Crackle
87		Ref. 88	Wheeze, crackle, squawk
89		Ref. 37	Wheeze, crackle
90		Ref. 37	
91		Ref. 15	Wheeze, crackle
92		Ref. 37	
93	Piezoelectric microphone		Unspecified
94	Electronic stethoscope	Refs. 95 and 96	Wheeze
97		Ref. 51	Wheeze, crackle, stridor
98	Unspecified	Unspecified	Crackle
99	Piezoelectronic microphone, electronic stethoscope		Wheeze, crackle, rhonchi
100	Accelerometer	Unspecified	Wheeze
101	Electronic stethoscope		Wheeze, crackle
102		Refs. 15 and 81	Bronchovesicular, normal and abnormal bronchial, crackle, wheeze, stridor, normal bronchophony, bronchophony by consolidation, normal and abnormal egophony
103	Digital stethoscope		Crackle

TABLE 1: *(continued)*

104	Electret microphone, pneumotachograph		Wheeze, crackle
105	Electret microphone, pneumotachograph		Wheeze
106	Piezoelectric microphone, electronic stethoscope		Wheeze, crackle, rhonchi
107	Electret microphone	Refs. 49 and 51	Wheeze
108	Electronic stethoscope		Crackle
109	Main microphone of a smartphone		Wheeze
110	Piezoelectric microphone, pneumotachograph		Wheeze, rhonchi
111	Electronic stethoscope		Wheeze, crackle
112	Electronic stethoscope		Unspecified
113		Ref. 15	Monophonic and polyphonic wheeze, crackle
114		Refs. 37 and 88	Wheeze, crackle
115	Electret microphone		Wheeze, crackle
116		Refs. 37, 50, and 68	Unspecified
117	Microphone, pneumotachograph		Wheeze

ACCP, American College of Clinical Pharmacy

developed other studies to monitor cardiac health using smartphones.[147,148]

In research proposed by Khan et al.,[149] a modified stethoscope and a smartphone were used to record lung sounds. The main aim was the early detection of bronchitis in children who live in rural areas of India. Lung sounds of the patients were recorded at the local pediatrician's hospital, and the lung sound file and case history were then sent by email to the hospital. A qualified medical practitioner carried out analysis of the sound signal.

In other studies, smartphones, including their camera and flash, have been used to obtain respiratory rate estimation at normal breathing rates.[148,150,151] Because breathing rate and heart rate can be measured directly by a finger's pulsatile flows,[148] a fingertip was placed in the lens of the smartphone to obtain the pulse signal.

Smartphones for medical research that have been developed during the last several years are known as mobile health (mHealth) apps. mHealth apps include the use of mobile devices for remote

TABLE 2: Heart sound types

Ref.	Data source		Heart sound type
	Sensor type	**Database**	
118	Electronic stethoscope	Moukadem et al.[118] database	80 Sounds: 40 pathological cardiac and 40 valvulopathies
119	Earphone, microphone, and IC recorder	Sun et al.[119] database	45 Normal sounds and 75 pathological
120	Electric stethoscope	Jiang et al.[120] database	Two abnormal sounds (unvalidated)
121	Unavailable	eGeneral Medical PCG database	Heart sounds S_1–S_4 and murmurs
122	Acoustic cardiography	Wang et al.[122] database	S_3 Sounds: 94 with hypertension, 109 with heart failure, and normal ejection fraction
123	Self-produced wireless electric stethoscope	Choi and Jiang[123] database	196 Normal and 293 abnormal sounds of heart valvular disorder
124	Electric transducer	Wang et al.[124] database	50 Normal sounds and 68 abnormal (heart overload, early diastolic, enhanced S_2)
125	Electric stethoscope	Middle Tennessee State University database	Ten normal and abnormal S_1 and S_2 sounds
126	Unavailable	Medical training database	Innocent and pathological murmurs
127	Electronic stethoscope	Online medical archives	Normal heart sounds from lung sounds
128	Cardiac microphone	Griffel et al.[128] recordings	100 Samples of coronary artery disease
129	Electronic stethoscope	Saraçoğlu[129] recordings	Healthy subjects and patients with cardiac valve disease, PS, or MS
130	Electronic stethoscope	Gharehbaghi et al.[130] recordings	100 Patients with VAS
131	Unavailable	Two data sets from heart sounds laboratory of the Texas Heart Institute	50 Heart sounds and murmurs
25	PCG	Database from Michigan University website	Arrhythmic nature of heart beat. Mitral regurgitation, aortic regurgitation, and patent ductus arteriosus
132	iPhone users and the iStethoscope	Two public data sets published in the PASCAL Classifying Heart Sounds Challenge	176 Records organized in four categories: normal, murmur, extra heart sound, and artifact

TABLE 2: *(continued)*

133	PCG	Zheng et al.[133] data set	80 Normal heart sounds and 167 systolic heart murmur samples segmented from 40 healthy volunteers and 67 patients
134	Stethoscope	Uğuz[134] recordings	120 Subjects with normal, pulmonary, and MS heart valve diseases
135	Electronic stethoscope	Data set of Massachusetts General Hospital	123 Patients: 38 normal controls, 37 MVP, 36 benign murmurs, five aortic disease, and seven miscellaneous conditions (tricuspid regurgitation, endocarditis, asymmetric septal hypertrophy)
136	Electronic stethoscope	Data collection of Real Hospital Portugues de Beneficencia, Brazil	84 Heart sounds, only identifications of murmurs
26	Electronic stethoscope	Randhawa and Singh[26] data recordings	144 Samples of normal, systolic murmur, and diastolic murmur signals
137	Electronic stethoscope	Tang et al.[137] data recordings	Three normal and 23 abnormal patients; murmurs found
138	Electronic stethoscope	Data set of the Children Heart Center of Tehran, Iran	40 Normal and 80 valvular and septal heart disease
139	Electronic stethoscope	Database from Rajaei Cardiovascular, Medical, and Research Center	25 Males and 25 females with different types of valve disease
140	Phonocardiographic sensor	Zhang et al.[140] data recording	225 Normal sounds and 180 abnormal sounds such as MS, ventricular septal defect, and aortic stenosis

MS, Mitral stenosis; MVP, mitral valve prolapse; PCG, phonocardiogram; PS, pulmonary stenosis; VAS, valvular aortic stenosis

monitoring of vital signals, disease prevention, acquisition and to send medical information and research, data visualization, and tracking of treatment progress. Nowadays, a vast array of mHealth apps are available on the market for constant monitoring of vital signs such as blood pressure, cardiac frequency, and oxygen saturation. Some publications document the use of smartphones for the diagnosis of diseases[152] and as a medical assistant,[153] among others uses.

mHealth apps have several benefits, especially for medical education.[154] In a study conducted by Low et al.[155] a team of trained doctors used an app[156] to significantly improve performance during a simulated cardiac arrest. Another study carried out by Buijink et al.[157] suggests that medical apps in clinical practice will significantly contribute to accessible and evidence-based health care and to improve practical clinical skills in medical education. Much work is needed by physicians, hospitals, and healthcare centers to establish appropriate regulatory procedures that ensures patient safety when a mHealth app is used.

With the current shortage of access to health

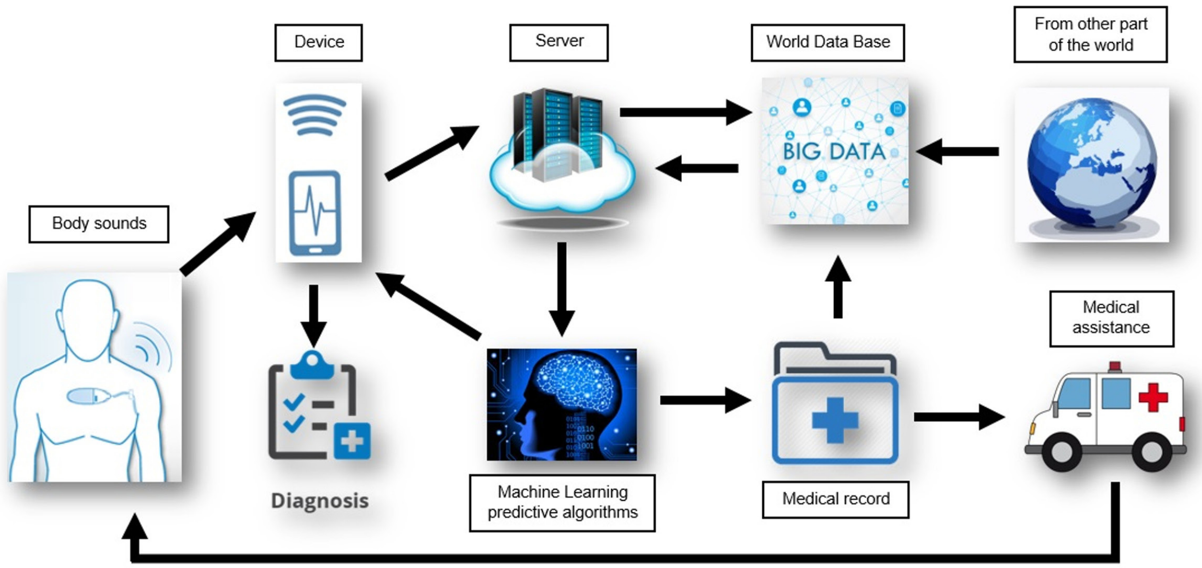

FIG. 8: Acoustic monitoring of the human body system

care, especially in countries with large populations, major health issues have emerged. For example, according to the WHO, 70% of population in India lives in rural areas,[158] but physicians and health-care resources are concentrated in urban areas. Such a situation creates the need to develop compact and easily accessible devices that can help to diagnose major pathologies, which is in line with the main objective of this review.

V. FUTURE PROSPECTS AND CONCLUSIONS

In this article, we analyzed a global system in which smartphones are used for monitoring, diagnosis, and giving medical support and assistance (should that become necessary) that is based on a large database. The value for this "big data" in health care today is limited to research, because its use requires a very specialized skill set; however, big data analytics has great potential in the health-care field.[159] Academic and research-focused health-care institutions are either experimenting with big data and already using it for advanced research projects. Some system details are given below.

Acoustic signals generated by the human body (e.g., lungs, heart, stomach) are acquired through sensors, and these sampled signals are sent to a server via smartphone. Feature extraction and machine-learning algorithms are applied to the signals online. Once these signals are analyzed, results of the analysis are sent to a medical record server that will be reviewed by specialist doctors and then sent to the global database. This database will include data recordings from others parts of the world to help refine the diagnosis through algorithms based on pattern recognition and artificial intelligence.

Subsequently, results of analyses are sent to the mobile device to provide a diagnosis of a patient's pathology. Owing to the availability of global positioning system (GPS) technology on mobile devices, the patient can potentially receive immediate medical assistance, for example in case of a medical emergency. This will benefit those living in rural areas. Figure 8 presents an overview of the proposed system. Other considerations include patient privacy and deployment of sensors, camera, GPS technology, internet access, and a team of specialist physicians who can validate the information and results that are received from the big database.[159]

Often, methods that health-care professionals use to analyze, process, and interpret data remain basic. Cutting-edge technology including machine-learning algorithms, natural language processing, and cognitive computing are needed to better understand human behavior. A large database system with GPS is proposed herein (Fig. 8).

ACKNOWLEDGMENTS

The Consejo Nacional de Ciencia y Tecnología (CONACyT- Mexico) and the advanced manufacturing research group of the Instituto Tecnológico y de Estudios Superiores de Monterrey (ITESM) funded this work.

REFERENCES

1. GBD 2015 Mortality and Causes of Death Collaborators. Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: A systematic analysis for the Global Burden of Disease Study 2015. Lancet. 2016;388(10053):1459–544. Available from: http://www.thelancet.com/pdfs/journals/lancet/PIIS0140-6736(16)31012-1.pdf /.
2. World Health Organization [homepage on the Internet]. Chronic obstructive pulmonary disease (COPD). Available from: http://www.who.int/mediacentre/factsheets/fs315/en/.
3. Lozano R, Naghavi M, Foreman K, Lim S, Shibuya K. Global and regional mortality from 235 causes of death for 20 age groups in 1990 and 2010: A systematic analysis for the Global Burden of Disease Study 2010. Lancet. 2013;380(9859):2095–128. Available from: https://ac.els-cdn.com/S0140673612617280/1-s2.0-S0140673612617280-main.pdf?_tid=95c9ebf2-18bf-11e8-8588-00000aab0f26&acdnat=1519407357_9aca8e71423dd2e43c9d0bb187ebfcf8/.
4. GOLD 2017. Global Strategy for the Diagnosis, Management and Prevention of COPD. Global Initiative for Chronic Obstructive Lung Disease. Available from: http://goldcopd.org.
5. World Health Organization [homepage on the Internet]. Global alliance against chronic respiratory diseases (GARD) basket: A package of information, surveillance tools and guidelines, to be offered as a service to countries. 2008. Available from: http://www.who.int/gard/publications/GARD_Basket_web.pdf.
6. Pearce N, Ait-Khaled N, Beasley R, Mallol J, Keil U, Mitchell E, Robertson C. Worldwide trends in the prevalence of asthma symptoms: Phase III of the International Study of Asthma and Allergies in Childhood (ISAAC). Thorax. 2007;62(9):758–66.
7. Respiratory Diseases in the World: Realities of Today–Opportunities for Tomorrow. Sheffield, UK: Forum of International Respiratory Societies. 2013. p. 1–35. Available from: https://www.ersnet.org/pdf/publications/firs-world-report.pdf.
8. World Health Organization. Global tuberculosis report 2016. Available from: http://apps.who.int/iris/bitstream/10665/250441/1/9789241565394-eng.pdf.
9. Centers for Disease Control and Prevention NC for HS. Underlying Cause of Death 1999–2013 on the CDC WONDER Online Database; released 2015. Data from the Multiple Cause of Death Files, 1999–2013, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program. 1999.
10. American Heart Association. Heart Disease and Stroke Statistics—2016 Update. Circulation. 2016;131(4):e38–360.
11. Goldberg RJ, Ciampa J, Lessard D, Meyer TE, Spencer FA. Long-term survival after heart failure. Arch Intern Med. 2007;167(5):490–6.
12. Henkel DM, Redfield MM, Weston SA, Gerber Y, Roger VL. Death in heart failure: A community community perspective. Circ Heart Failure. 2008;1(2):91–7.
13. Mehta PA, Dubrey SW, McIntyre HF, Walker DM, Hardman SMC, Sutton GC, McDonagh TA, Cowie MR. Mode of death in patients with newly diagnosed heart failure in the general population. Eur J Heart Failure. 2008;10(11):1108–16.
14. Murphy SL, Xu J, Kochanek KD. Deaths: Final data for 2010. National Vital Statistics Reports. Natl Center Health Stat. 2013;61(4):1–117.
15. Lehrer S. Understanding Lung Sounds (with audio CD). Philadelphia: WB Saunders; 2002.
16. Palaniappan R, Sundaraj K, Ahamed NU. Machine learning in lung sound analysis: A systematic review. Biocybern Biomed Eng. 2013;33(3):129–35.
17. Sarkar M, Madabhavi I, Niranjan N, Dogra M. Auscultation of the respiratory system. Ann Thorac Med. 2015;10(3):158–68.
18. Forgacs P, Nathoo AR, Richardson HD. Breath sounds. Thorax. 1971;26(3):288–95.
19. Fuster V, Walsh RA, Harrington RA. Hurst's the heart manual of cardiology. 13th Ed. New York: McGraw-Hill Medical; 2011.
20. Waider W, Craige E. First heart sound and ejection sounds: Echocardiographic and phonocardiographic correlation with valvular events. Am J Cardiol. 1975;35(3):346–56.
21. Hirschfeld S, Liebman J, Borkat G, Bormuth C. Intracardiac pressure-sound correlates of echographic aortic valve closure. Circulation. 1977;55(4):602–4.
22. Reddy PS, Salerni R, Shaver JA. Normal and abnormal heart sounds in cardiac diagnosis: Part II. Diastolic sounds. Curr Probl Cardiol. 1985;10(4):7–55.
23. Goldblatt A, Aygen M, Braunwald E. Hemodynamic-

phonocardiographic correlations of the fourth heart sound in aortic stenosis. Circulation. 1962;26:92–8.
24. Yan Z, Jiang Z, Miyamoto A, Wei Y. The moment segmentation analysis of heart sound pattern. Comput Meth Progr Biomed. 2010;98(2):140–50.
25. Lubaib P, Munner KA. The heart defect analysis based on PCG signals using pattern recognition techniques. Procedia Technol. 2016;24:1024–31.
26. Randhawa SK, Singh M. Classification of heart sound signals sing multi-modal features. Procedia Comput Sci. 2015;58:165–71.
27. Arnott PJ, Pfeiffer GW, Tavel ME. Spectral analysis of heart sounds: Relationships between some physical characteristics and frequency spectra of first and second heart sounds in normals and hypertensives. J Biomed Eng. 1984;6(2):121–8.
28. Reichert S, Gass R, Brandt C, Andrès E. Analysis of respiratory sounds: State of the art. Clin Med Circ Respir Pulm Med. 2008;2:45–58.
29. Bishop PJ. Evolution of the stethoscope. J Royal Soc Med. 1980;73:448–56.
30. Roguin A. The man behind the stethoscope. Clin Med Res. 2006;4(3):230–5.
31. Tavel ME. Cardiac auscultation: A glorious past---and it does have a future! Circulation. 2006;113(9):1255–9.
32. Sovijärvi ARA, Vanderschoot J, Earis JE. Standardization of computerized respiratory sound analysis. Eur Respir Rev. 2000;10(77):585–6.
33. Abella M, Formolo J, Penney DG. Comparison of the acoustic properties of six popular stethoscopes. J Acoust Soc Am. 1992;91(4):2224–8.
34. Larry F. Physical characteristics of sound and hearing. Am J Cardiol. 1971;28(2):130–3.
35. Gurung A, Scrafford CG, Tielsch JM, Levine OS, Checkley W. Computerized lung sound analysis as diagnostic aid for the detection of abnormal lung sounds: A systematic review and meta-analysis. Respir Med. 2011;105:1396–403.
36. Gross V, Hadjileontiadis LJ, Penzel T, Koehler U, Volgelmeier C. Multimedia Database Marburg Respiratory Sounds (MARS). Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biological Society; 2003 Sep 17–21; Cancun, México, p. 456–7.
37. The R.A.L.E. Repository [cited 2017 Apr 18]. Available from: http://www.rale.ca/Reference.htm.
38. Brown AS, Harvey DM, Jamieson G, Graham DR. Phi-SAS: A low-cost medical system for the observation of respiratory dysfunction. IEE Seminar on Appropriate Medical Technology for Developing Countries. London, UK. 6 Feb 2002. 2002;1–5.
39. Pinho C, Oliveira D, Oliveira A, Dinis J, Marques A. LungSounds@UA interface and multimedia database. Procedia Technol. 2012;5:803–11.
40. Dinis J, Campos G, Rodrigues J, Marques A. Respiratory sound annotation software. Proceedings of the International Conference on Health Informatics; 2012 Feb 1–4; Vilamoura, Algarve, Portugal. p. 183–8.
41. Semedo J, Oliveira A, Machado A, Moreira J, Rodrigues J, Aparício J, Pasterkamp H, Jesus LM, Marques A. Computerised Lung Auscultation—Sound Software (CLASS). Procedia Comput Sci. 2015;64:697–704.
42. Physionet 2016. Classification of normal/abnormal heart sound recordings: The PhysioNet/Computing in Cardiology Challenge 2016 [accessed September 4, 2017]. Available from: https://physionet.org/challenge/2016/.
43. Clifford G, Liu C, Moody B, Springer D, Silva I, Li Q, Mark RG. Classification of normal/abnormal heart sound recordings: The PhysioNet/Computing in Cardiology Challenge 2016. Computing in Cardiology Conference (CinC); 2016 Sep 11–14; Vancouver, BC, Canada. p. 609–12.
44. Bentley P, Nordehn G, Coimbra M, Mannor S, Getz R. The PASCAL Classifying Heart Sounds Challenge 2011. Available from: http://www.peterjbentley.com/heartchallenge/.
45. Heart Sound and Murmur Library [database on the Internet]. University of Michigan Health System [accessed February 10, 2017]. Available from: http://www.med.umich.edu/lrc/psb_open/html/repo/primer_heartsound/primer_heartsound.html.
46. Cardiac Auscultation of Heart Murmurs [database on the Internet]. Raleigh, NC: eGeneral Medical Inc. [accessed February 16, 2017]. Available from: http://www.egeneralmedical.com/listohearmur.html.
47. Easy Auscultation Training | Heart and Lung Sounds [homepage on the Internet]. Westborough, MA: MedEdu LLC. [accessed February 16, 2017]. Available from: https://www.easyauscultation.com/.
48. Practical Clinical Skills [homepage on the Internet]. Westborough, MA: Medical Training and Simulation LLC. [accessed February 16, 2017]. Available from: https://www.practicalclinicalskills.com/.
49. 50 Heart and Lung Sounds Library: 3MTM Littmann® Stethoscopes: 3M Gulf [homepage on the Internet]. 3M: Master Classic and TeleSteth [accessed February 16, 2017]. Available from: http://solutions.3mae.ae/wps/portal/3M/en_AE/3M-Littmann-EMEA/stethoscope/littmann-learning-institute/heart-lung-sounds/.
50. Auscultation Assistant. Breath sounds [homepage on the Internet]. University of California, Los Angeles [accessed February 16, 2017]. Available from: http://www.wilkes.med.ucla.edu/lungintro.htm.
51. SoundCloud [accessed February 16, 2017]. Available from: https://soundcloud.com/search?q=lung sounds.
52. Tilkian A, Conover M. Understanding heart sounds and murmurs: With an introduction to lung sounds. 4th ed. Philadelphia: WB Saunders; 2001.
53. Hashemi A, Arabalibiek H, Agin K. Classification of wheeze sounds using wavelets and neural networks.

Proceedings of International Conference on Biomedical Engineering and Technology. Singapore: IACSIT Press; 2011. p. 127–31.
54. Jin F, Krishnan S, Sattar F. Adventitious sounds identification and extraction using temporal-spectral dominance-based features. IEEE Trans Biomed Eng. 2011;58(11):3078–87.
55. Wilkins R, Hodgkin J, Lopez B. Fundamentals of lung and heart sounds. 3rd Ed. St. Louis, MO: Mosby; 2004.
56. Ayari F, Ksouri M, Alouani A. A new scheme for automatic classification of pathologic lung sounds. Int J Comput Sci. 2012;9(4):448–58.
57. Emmanouilidou D, Patil K, West J, Elhilali M. A multiresolution analysis for detection of abnormal lung sounds. Conference Proceedings of the 2012 Annual International Conference of the IEEE Engineering in Medicine and Biological Society; 2012 Aug 28–Sep 1; San Diego, California. p. 3139–42.
58. Himeshima M, Yamashita M, Matsunaga S, Miyahara S. Detection of abnormal lung sounds taking into account duration distribution for adventitious sounds. Conference Proceedings of the 20th European Conference on Signal Processing; 2012 Aug 27–31; Bucharest, Romania. p. 1821–5.
59. Jin F, Sattar F, Krishan S. Log-frequency spectrogram for respiratory sound monitoring. IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP); 2012 Mar 25–30; Kyoto, Japan. p. 597–600.
60. Zhenzhen L, Xiaoming W. Wheeze detection using fractional Hilbert transform in the time domain. IEEE Biomedical Circuits and Systems Conference (BioCAS); 2012 Nov 28–30; Hsinchu, Taiwan. p. 316–9.
61. Maciuk M, Kuniszyk–Józkowiak W, Doboszynska A, Maciuk M. Analysis of lung auscultatory phenomena using the Wigner-Ville Distribution. Ann Univ Marie Curie Sklodowska. 2012;12(1):7–16.
62. Mayorga P, Druzgalski C, González OH, López HS. Modified classification of normal lung sounds applying quantile vectors. Conference Proceedings of the 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2012 Sep 28– Aug 1; San Diego, California. p. 4262–5.
63. Sakai T, Kato M, Miyahara S, Kiyasu S. Robust detection of adventitious lung sounds in electronic auscultation signals. The 21st International Conference on Pattern Recognition (ICPR); 2012 Nov 11–15; Tsukuba, Japan. p. 1993–6.
64. Wang B, Miao L, Dong H, Zheng Z. The research of lung sound signals based on cepstrum analysis. Proceedings of the International Conference of the IEEE Biomedical Engineering and Biotechnology Society; 2012 May 28–30; Macao, China. p. 934–8.
65. Xie S, Jin F, Krishnan S, Sattar F. Signal feature extraction by multi-scale PCA and its application to respiratory sound classification. Med Biol Eng Comput. 2012;50(7):759–68.
66. Zhenzhen L, Xiaoming W, Minghui D. A novel method for feature extraction of crackles in lung sounds. Proceedings of the 5th International Conference of the IEEE Biomedical Engineering and Informatics (BMEI) Society; 2012 Oct 16–18; Chongqing, China. p. 399–402.
67. Abbasi S, Derakhshanfar R, Abbasi A, Sarbaz Y. Classification of normal and abnormal lung sounds using neural network and support vector machines. Proceedings of the 21st Iranian Conference of the IEEE Conference on Electrical Engineering (ICEE); 2013 May 14–16; Mashhad, Iran. p. 1–4.
68. Arnall D. Pulmonary breath sounds [accessed March 10, 2017]. Available from: http://faculty.etsu.edu/arnall/www/public_html/heartlung/breathsounds/contents.html.
69. Becker KW, Scheffer C, Blanckenberg MM, Diacon AH. Analysis of adventitious lung sounds originating from pulmonary tuberculosis. Proceedings of the 35th Annual International Conference of the IEEE Biomedical Engineering and Biotechnology Society; 2013 Jul 3–7; Osaka, Japan. p. 4334–7.
70. Charleston-Villalobos S, Castaneda-Villa N, Gonzalez-Camarena R, Mejia-Avila M, Aljama-Corrales T. Adventitious lung sounds imaging by ICA-TVAR scheme. Proceedings of the 35th Annual International Conference of the IEEE Biomedical Engineering and Biotechnology Society; 2013 Jul 3–7; Osaka, Japan. p. 1354–7.
71. Emrani S, Krim H. Wheeze detection and location using spectro-temporal analysis of lung sounds. Proceedings of the 29th Southern Conference of the IEEE Biomedical Engineering Conference (SBEC); 2013 May 3–5; Miami, FL. p. 37–8.
72. Lozano M, Fiz JA, Jané R. Estimation of instantaneous frequency from empirical mode decomposition on respiratory sounds analysis. Proceedings of the 35th Annual International Conference of the IEEE Biomedical Engineering and Biotechnology Society; 2013 Jul 3–7; Osaka, Japan. p. 981–4.
73. Sánchez Morillo D, León Jiménez A, Moreno SA. Computer-aided diagnosis of pneumonia in patients with chronic obstructive pulmonary disease. J Am Med Inform Assoc. 2013;20(e1):e111–7.
74. Oliveira A, Pinho C, Dinis J, Oliveira D, Marques A. Automatic wheeze detection and lung function evaluation: A preliminary study. Proceedings of the 6th International Conference on Health Informatics; 2013 Feb 11–14; Barcelona, Spain. p. 323–6.
75. Palaniappan R, Sundaraj K. Respiratory sound classification using cepstral features and support vector machine. Proceedings of the IEEE Conference on Recent Advances in Intelligent Computational Systems (RAICS); 2013 Dec 19–21; Trivandrum, India. p. 132–6.
76. Ponte DF, Moraes R, Hizume DC, Alencar AM. Characterization of crackles from patients with fibrosis, heart

failure and pneumonia. Med Eng Phys. 2013;35:448–56.
77. Serbes G, Sakar CO, Kahya YP, Aydin N. Pulmonary crackle detection using time-frequency and time-scale analysis. Digit Signal Process. 2013;23(3):1012–21.
78. Yu C, Tsai TH, Huang SI, Lin CW. Soft stethoscope for detecting asthma wheeze in young children. Sensors. 2013;13(6):7399–413.
79. Chen X, Shao J, Long Y, Que C, Zhang J, Fang J. Identification of Velcro rales based on Hilbert–Huang transform. Phys A Stat Mechan Appl. 2014;401:34–44.
80. Emrani S, Gentimis T, Krim H. Persistent homology of delay embeddings and its application to wheeze detection. IEEE Signal Process Lett. 2014;21(4):459–63.
81. Auscultation skills: Breath and heart sounds. 4th Ed. Philadelphia: Lippincott Williams and Wilkin; 2009.
82. Wrigley D. Heart and Lung Sounds: Reference Library. Eau Claire, WI: PESI HealthCare; 2011.
83. Içer S, Gengeç Ş. Classification and analysis of non-stationary characteristics of crackle and rhonchus lung adventitious sounds. Digit Signal Process. 2014;28:18–27.
84. Jin F, Sattar F, Goh DY. New approaches for spectro-temporal feature extraction with applications to respiratory sound classification. Neurocomputing. 2014;123:362–71.
85. Lin BS, Yen TS. An FPGA-based rapid wheezing detection system. Int J Environ Res Public Health. 2014;11(2):1573–93.
86. Mendes L, Carvalho P, Teixeira CA, Paiva RP, Henriques J. Robust features for detection of crackles: An exploratory study. Proceedings of the 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2014 Aug 26–30; Chicago, IL. p. 1473–6.
87. Mondal A, Bhattacharya P, Saha G. Detection of lung status using morphological complexities of respiratory sounds. Sci World J. 2014;2014:1–9.
88. Audio and Bio Signal Processing Lab [accessed March 10, 2017]. Available from: http://www.ecdept.iitkgp.ernet.in/index.php/home/labs/bio-sig-proc.
89. Orjuela-Cañón AD, Gómez-Cajas DF, Jiménez-Moreno R. Artificial Neural Networks for Acoustic Lung Signals Classification. In: Bayro-Corrochano E, Hancock E, Eds. Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications (CIARP) 2014: Proceedings of the 19th Ibero-American Congress on Pattern Recognition; 2014 Nov 2–5; Puerto Vallarta, Mexico. New York: Springer; 2014. p. 214–21.
90. Palaniappan R, Sundaraj K, Sundaraj S. A comparative study of the SVM and K-nn machine learning algorithms for the diagnosis of respiratory pathologies using pulmonary acoustic signals. BMC Bioinformatics. 2014;15(1):223.
91. Tocchetto MA, Bazanella AS, Guimaraes L, Fragoso JL, Parraga A. An embedded classifier of lung sounds based on the wavelet packet transform and ANN. Proceedings of the 19th World Congress of the International Federation of Automatic Control; 2014 Aug 24–29; Cape Town, South Africa. p. 2975–80.
92. Uysal S, Uysal H, Bolat B, Yildirim T. Classification of normal and abnormal lung sounds using wavelet coefficients. Proceedings of the 22nd Conference of the IEEE Signal Processing and Communications Applications; 2014 Apr 23–25; Trabzon, Turkey. p. 2138–41.
93. Yamashita M, Himeshima M, Matsunaga S. Robust classification between normal and abnormal lung sounds using adventitious-sound and heart-sound models. Proceedings of International IEEE Conference on Acoustics, Speech, and Signal Processing (ICASSP); 2014 May 4–9; Florence, Italy. p. 4418–22.
94. Li J, Hong Y. Wheeze detection algorithm based on spectrogram analysis. Proceedings of the 8th International IEEE Symposium on Computational Intelligence and Design (ISCID); 2015 Dec 12–13; Hangzhou, China. p. 318–22.
95. ATS: American Thoracic Society [accessed February 18, 2017]. Available from: http://www.thoracic.org/.
96. COPD Education and Patient Education Materials of the COPD Foundation [accessed February 18, 2017]. Available from: https://www.copdfoundation.org/Learn-More/Educational-Materials/Downloads-Library.aspx.
97. Liu X, Ser W, Zhang J, Goh DY. Detection of adventitious lung sounds using entropy features and a 2-D threshold setting. Proceedings of the 10th International IEEE Conference on Information, Communications, and Signal Processing (ICICS); 2015 Dec 2–4; Singapore. p. 1–5.
98. Maruf SO, Azhar MU, Khawaja SG, Akram MU. Crackle separation and classification from normal respiratory sounds using Gaussian Mixture Model. Proceedings of the 10th International IEEE Conference on Industrial and Information Systems (ICIIS); 2015 Dec 18–20; Peradeniya, Sri Lanka. p. 267–71.
99. Matsutake S, Yamashita M, Matsunaga S. Abnormal respiration detection by considering correlation of observation of adventitious sounds. Proceedings of the 23rd IEEE European Signal Processing Conference (EUSIPCO); 2015 Aug 31–Sept 4; Nice, France. p. 634–8.
100. Mazić I, Bonković M, Džaja B. Two-level coarse-to-fine classification algorithm for asthma wheezing recognition in children's respiratory sounds. Biomed Signal Process Control. 2015;21:105–18.
101. Mendes L, Vogiatzis IM, Perantoni E, Kaimakamis E, Chouvarda I, Maglaveras N, Tsara V, Teixera C, Carvalho P, Henriques J, Paiva RP. Detection of wheezes using their signature in the spectrogram space and musical features. Proceedings of the 37th Annual International IEEE Conference on Engineering in Medicine and Biology Society; 2015 Aug 25–29; Milan, Italy. p. 5581–4.
102. Oweis RJ, Abdulhay EW, Khayal A, Awad A. An alternative respiratory sounds classification system utilizing artificial neural networks. Biomed J. 2015;38(2):153–61.

103. Pinho C, Oliveira A, Jácome C, Rodrigues J, Marques A. Automatic crackle detection algorithm based on fractal dimension and box filtering. Procedia Comput Sci. 2015;64:705–12.
104. Sen I, Saraclar M, Kahya YP. A Comparison of SVM- and GMM-based classifier configurations for diagnostic classification of pulmonary sounds. IEEE Trans Biomed Eng. 2015;62(7):1768–76.
105. Ulukaya S, Sen I, Kahya YP. Feature extraction using time-frequency analysis for monophonic-polyphonic wheeze discrimination. Proceedings of the 37th Annual IEEE International Conference on Engineering in Medicine and Biology Society; 2015 Aug 25–29; Milan, Italy. p. 5412–5.
106. Umeki S, Yamashita M, Matsunaga S. Classification between normal and abnormal lung sounds using unsupervised subject-adaptation. Proceedings of the Annual IEEE Summit and Conference on Asia-Pacific Signal and Information Processing Association (APSIPA); 2015 Dec 16–19; Hong Kong, China. p. 213–6.
107. Wisniewski M, Zielinski TP. Joint application of audio spectral envelope and tonality index in an E-asthma monitoring system. IEEE J Biomed Health Inform. 2015;19(3):1009–18.
108. Zhang K, Wang X, Han F, Zhao H. The detection of crackles based on mathematical morphology in spectrogram analysis. Technol Health Care. 2015;23(s2):S489–94.
109. Bokov P, Mahut B, Flaud P, Delclaux C. Wheezing recognition algorithm using recordings of respiratory sounds at the mouth in a pediatric population. Comput Biol Med. 2016;70:40–50.
110. Lozano M, Fiz JA, Jané R. Automatic differentiation of normal and continuous adventitious respiratory sounds using ensemble empirical mode decomposition and instantaneous frequency. IEEE J Biomed Health Inform. 2016;20(2):486–97.
111. Mendes L, Vogiatzis IM, Perantoni E, Kaimakamis E, Chouvarda I, Maglaveras N, Henriques J, Carvalho P, Paiva RP. Detection of crackle events using a multi-feature approach. Proceedings of the 38th Annual International IEEE Conference on Engineering in Medicine and Biology Society; 2016 Aug 16–20; Orlando, FL. p. 3679–83.
112. Nakamura N, Yamashita M, Matsunaga S. Detection of patients considering observation frequency of continuous and discontinuous adventitious sounds in lung sounds. Proceedings of the 37th Annual IEEE International Conference on Engineering in Medicine and Biology Society; 2016 Aug 16–20; Orlando, FL. p. 3457–60.
113. Naves R, Barbosa BH, Ferreira DD. Classification of lung sounds using higher-order statistics: A divide-and-conquer approach. Comput Methods Programs Biomed. 2016;129:12–20.
114. Sengupta N, Sahidullah M, Saha G. Lung sound classification using cepstral-based statistical features. Comput Biol Med. 2016;75:118–29.
115. Ulukaya S, Serbes G, Sen I, Kahya YP. A lung sound classification system based on the rational dilation wavelet transform. Proceedings of the 38th Annual IEEE International Conference on Engineering in Medicine and Biology Society; 2016 Aug 16–20; Orlando, FL. p. 3745–8.
116. Rizal A, Hidayat R, Nugroho HA. Lung sound classification using empirical mode decomposition and the Hjorth descriptor. Am J Appl Sci. 2017;14(1):166–73.
117. Shimoda T, Obase Y, Nagasaka Y, Nakano H, Ishimatsu A, Kishikawa R, Iwanaga T. Lung sound analysis helps localize airway inflammation in patients with bronchial asthma. J Asthma Allergy. 2017;10:99–108.
118. Moukadem A, Dieterlen A, Hueber N, Brandt C. A robust heart sounds segmentation module based on S-transform. Biomed Signal Process Control. 2013;8(3):273–81.
119. Sun S, Jiang Z, Wang H, Fang Y. Automatic moment segmentation and peak detection analysis of heart sound pattern via short-time modified Hilbert transform. Comput Meth Programs Biomed. 2014;114(3):219–30.
120. Jiang Z, Choi S. A cardiac sound characteristic waveform method for in-home heart disorder monitoring with electric stethoscope. Expert Syst Appl. 2006;31(2):286–98.
121. Varghees VN, Ramachandran KI. A novel heart sound activity detection framework for automated heart sound analysis. Biomed Signal Process Control. 2014;13(1):174–88.
122. Wang S, Lam YY, Liu M, Fang F, Wang J, Shang Q, Sun JP, Sanderson JE, Yu CM. Acoustic cardiography helps to identify heart failure and its phenotypes. Int J Cardiol. 2013;167(3):681–6.
123. Choi S, Jiang Z. Cardiac sound murmurs classification with autoregressive spectral analysis and multi-support vector machine technique. Comput Biol Med. 2010;40(1):8–20.
124. Wang Y, Li W, Zhou J, Li X, Pu Y. Identification of the normal and abnormal heart sounds using wavelet-time entropy features based on OMS-WPD. Future Gen Comput Sys. 2014;37:488–95.
125. Yan Z, Jiang Z, Miyamoto A, Wei Y. The moment segmentation analysis of heart sound pattern. Comput Meth Prog Biomed. 2010;98(2):140–50. Available from: http://dx.doi.org/10.1016/j.cmpb.2009.09.008.
126. Finley J, Caissie R, Nicol P, Newman A, Hoyt B, MacAulay D. New auditory training program rapidly teaches students to distinguish innocent and pathological murmurs with 90% accuracy. Can J Cardiol. 2010;26(1):139D.
127. Chao CT, Maneetien N, Wang CJ, Chiou JS. Performance evaluation of heart sound cancellation in FPGA hardware implementation for electronic stethoscope. Sci World J. 2014;2014:1–7.
128. Griffel B, Zia MK, Fridman V, Saponieri C, Semmlow JL. Path length entropy analysis of diastolic heart sounds. Comput Biol Med. 2013;43:1–13.

129. Saraçoğlu R. Hidden Markov model-based classification of heart valve disease with PCA for dimension reduction. Eng Appl Artif Intel. 2012;25(7):1523–8.
130. Gharehbaghi A, Ekman I, Ask P, Nylander E, Janerot-Sjoberg B. Assessment of aortic valve stenosis severity using intelligent phonocardiography. Int J Cardiol. 2015;198:58–60.
131. Patidar S, Pachori RB. Classification of cardiac sound signals using constrained tunable-Q wavelet transform. Expert Sys Appl. 2014;41(16):7161–70.
132. Deng SW, Han JQ. Towards heart sound classification without segmentation via autocorrelation feature and diffusion maps. Future Gen Comput Sys. 2016;60:13–21.
133. Zheng Y, Guo X, Ding X. A novel hybrid energy fraction and entropy-based approach for systolic heart murmurs identification. Expert Sys Appl. 2015;42(5):2710–21.
134. Uğuz H. Adaptive neuro-fuzzy inference system for diagnosis of the heart valve diseases using wavelet transform with entropy. Neur Comput Appl. 2012;21(7):1617–28.
135. Springer DB, Tarassenko L, Clifford GD. Logistic regression-HSMM-based heart sound segmentation. IEEE Trans Biomed Eng. 2016;63(4):822–32.
136. Castro A, Vinhoza TT, Mattos SS, Coimbra MT. Heart sound segmentation of pediatric auscultations using wavelet analysis. Proceedings of the 35th Annual IEEE International Conference on Engineering in Medicine and Biology Society; 2013 Jul 3–7; Osaka, Japan. p. 3909–12.
137. Tang H, Li T, Qiu T, Park Y. Segmentation of heart sounds based on dynamic clustering. Biomed Signal Proc Control. 2012;7(5):509–16.
138. Gharehbaghi A, Dutoit T, Sepehri A, Hult P, Ask P. An automatic tool for pediatric heart sounds segmentation. Proceedings of the 2011 IEEE Computing in Cardiology Conference; Hangzhou, China. p. 37–40.
139. Naseri H, Homaeinezhad MR. Detection and boundary identification of phonocardiogram sounds using an expert frequency-energy based metric. Ann Biomed Eng. 2013;41(2):279–92.
140. Zhang W, Guo X, Yuan Z, Zhu X. Heart sound classification and recognition based on EEMD and correlation dimension. J Mech Med Biol. 2014;14(4):1450046.
141. Melbye H. Auscultation of the lungs: Still a useful examination? [Lungeauskultasjonen—Forsatt en nytttig undersokelse?]. Tidsskr Nor Laegeforen. 2001;121(4):451–4.
142. Murphy RL. In defense of the stethoscope. Respir Care. 2008;53(3):355–69.
143. Pasterkamp H, Kraman SS, Wodicka GR. Respiratory sounds: Advances beyond the stethoscope. Am J Respir Crit Care Med. 1997;156(3):974–87.
144. Sánchez Morillo D, Astorga Moreno S, Fernández Granero MÁ, León Jiménez A. Computerized analysis of respiratory sounds during COPD exacerbations. Comput Biol Med. 2013;43(7):914–21.
145. Mussell MJ. The need for standards in recording and analysing respiratory sounds. Med Biol Eng Comput. 1992;30(2):129–39.
146. Reyes BA, Reljin N, Chon KH. Tracheal sounds acquisition using smartphones. Sensors. 2014;14:13830–50.
147. Scully CG, Lee J, Meyer J, Gorbach AM, Granquist-Fraser D, Mendelson Y, Chon KH. Physiological parameter monitoring from optical recordings with a mobile phone. IEEE Trans Biomed Eng. 2012;59(2):303–6.
148. Nam Y, Kong Y, Reyes B, Reljin N, Chon KH. Monitoring of heart and breathing rates using dual cameras on a smartphone. PLoS ONE. 2016;11(3):e0151013.
149. Khan SI, Jawarkar NP, Ahmed V. Cell phone based remote early detection of respiratory disorders for rural children using modified stethoscope. Proceedings of the International Conference on Communication Systems and Network Technologies (CSNT); 2012 May 11–13; Rajkot, India. p. 936–40.
150. Lázaro J, Nam Y, Gil E, Laguna P, Chon KH. Smartphone-camera-acquired pulse photoplethysmographic signal for deriving respiratory care. Proceedings of the 8th European Study Group on Cardiovascular Oscillations (ESGCO); 2014 May 25–28; Trento, Italy. p. 121–2.
151. Nam Y, Lee J, Chon KH. Respiratory rate estimation from the built-in cameras of smartphones and tablets. Ann Biomed Eng. 2014;42(4):885–98.
152. Szanto Z, Benko I, Jakab L, Szalai G, Vereczkei A. The use of a smartphone application for fast lung cancer risk assessment. Eur J Cardio Thoracic Surg. 2017;51(6):1171–6.
153. Årsand E, Frøisland DH, Skrøvseth SO, Chomutare T, Tatara N, Hartvigsen G, Tufano JT. Mobile health applications to assist patients with diabetes: Lessons learned and design implications. J Diabetes Sci Technol. 2012;6(5):1197–206.
154. Ventola CL. Mobile devices and apps for health care professionals: Uses and benefits. Pharmacol Ther. 2014;39(5):356–64.
155. Low D, Clark N, Soar J, Padkin A, Stoneham A, Perkins GD, Nolan J. A randomised control trial to determine if use of the iResus© application on a smart phone improves the performance of an advanced life support provider in a simulated medical emergency. Anaesthesia. 2011;66(4):255–62.
156. Resuscitation Council (UK) Trading, Cranworth Medical Ltd. iResus Application. Available from: https://play.google.com/store/apps/details?id=cranworth.com.iresus&hl=es.
157. Buijink AW, Visser BJ, Marshall L. Medical apps for smartphones: Lack of evidence undermines quality and safety. Evid Based Med. 2013;18(3):90–2.
158. Office of the Registrar General & Census Commissioner, India [homepage on the Internet]. Available from: http://www.dataforall.org/dashboard/censusinfoindia_pca/.
159. Raghupathi W, Raghupathi V. Big data analytics in healthcare: Promise and potential Health Inform Sci Syst. 2014;2(1):1–10.