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REVIEW ARTICLE

Approaches for Respiratory Sound Analysis in Identification of Respiratory Diseases

Arunkumar Ram [1*], Ghanshyam Jindal [1], Uttam Bagal [1], Gajanan Nagare [2]

[1] *Department of Biomedical Engineering, MGM's College of Engineering & Technology, Navi Mumbai, India*

[2] *Department of Biomedical Engineering, Vidyalankar Institute of Technology, Mumbai, India*

*Corresponding Author: Arunkumar Ram
Email: arunkumar.ram@gmail.com

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Abstract

Purpose: Medical professionals throughout the world prefer to use conventional stethoscopes to listen to respiratory sounds. Listening to respiratory sounds through stethoscopes is a subjective matter, and proper diagnosis of the disease depends on the skills and ability of the doctor. Computerized analysis of respiratory sounds can help doctors and researchers to characterize different abnormal respiratory patterns and make informed decisions.

Materials and Methods: This study includes previously reported work in different normal and abnormal respiratory sounds. The IEEE, PubMed, Google Scholar and Elsevier databases were searched and studies with the keywords of lung sound analysis, respiratory sound analysis, and respiratory sound classification were included. Detailed characteristics of normal and abnormal respiratory sounds are mentioned. In addition, Time-amplitude characteristics of different respiratory sound plots are obtained using MATLAB and ICBHI database. This study systematically discusses different approaches for respiratory sound analysis like visual analysis of the time-amplitude signals, frequency analysis, and spectral analysis using fast Fourier transform, statistical analysis, and machine learning approach. A list of relevant datasets is mentioned that can help researchers to do further analysis in this domain.

Results: The careful observations and analysis show the possibility of predicting respiratory diseases by extracting suitable parameters such as the frequency response and spectral characteristics of the signal. Power spectral density can help us to calculate the maximum, median frequency over an extended period. Using machine learning we can estimate the energy, entropy, spectral features, and wavelets of the signals.

Conclusion: Computer-based respiratory sound analysis can help medical professionals in making informed decisions. This will help in early diagnosis and devise effective treatment plans for the patients.

Keywords: Respiratory Sound Analysis; Respiratory Sound Classification; Adventitious Respiratory Sounds; Datasets; Spectral Analysis; Time Frequency Analysis.

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1. Introduction

According to World Health Organization (WHO) data (2019), the third leading cause of death worldwide is due to respiratory diseases. Close to 6% of deaths happened globally due to Chronic Obstructive Pulmonary Disease (COPD). Lower Respiratory Tract Infection (LRTI) happens to be the fourth leading cause of death claiming 2.6 million lives globally [1]. Some of the factors leading to an increase in respiratory diseases are due to the increased consumption of tobacco and cigarette smoking, the adoption of the western lifestyle, and an increase in urbanization causing a release of toxic fumes into the environment [2]. The increase in the prevalence of respiratory disease poses a health risk to patients and put a lot of social and economic burden on the existing healthcare infrastructure for a developing country like India [3]. In the last two decades, there have been significant efforts in the timely and early diagnosis of respiratory diseases, and efforts are in developing systems that can help clinicians in providing timely interventions [4].

Lung auscultation is an important examination and helps physicians in diagnosing respiratory disorders. In the early 1800, Rene-Theophile-Hyacinthe-Laennec [5] invented the stethoscope. Since then, the stethoscope has been used by doctors and clinicians throughout the world for lung and heart auscultation. In 1817, Laennec [5] demonstrated the early prototype of the stethoscope consisting of a cone made up of 24 sheets of paper. Since then, researchers including Bowles, Sprague, Rapport and Groom [5] tried to modify the original design. In 1855 Dr. George Cammann [5] introduced the first binaural stethoscope consisting of two tubes for the earpiece.

Although stethoscopes have been in mainstream for listening to lung and respiratory sounds, it is a subjective matter as the clinical diagnosis depends on the doctor's experience, knowledge, and judgment. There is a limited application of stethoscope in research due to inherent inter-observer variability and differences in the interpretation of the respiratory sounds from physician to physician [6]. This limitation can be overcome by using electronic auscultation and automated classification of recorded respiratory sounds. Digital recording of the respiratory sounds and its subsequent analysis is not only reliable but also helps in the quantitative analysis of respiratory disease.

2. Normal and Abnormal Respiratory Sounds

Normal respiratory sounds are classified based on the location of the chest from where they are heard or generated. These respiratory sounds may have different characteristics like time duration, frequency, and intensity or amplitude of signal. The characteristics of normal respiratory sounds are described below.

2.1. Normal Respiratory Sounds

2.1.1. Vesicular Sounds

Normal vesicular sounds are characterized as being soft and non-musical, and are prominently heard during the inspiration and early expiration phase. The frequency heard is higher in the inspiration as compared to the expiration phase. Vesicular sounds have a longer duration in the inspiration phase as compared to expiration. These sounds have a low frequency with a drop in energy around 100 Hz-200 Hz [7]. Time-amplitude plot for normal respiratory sound is shown in Figure 1.

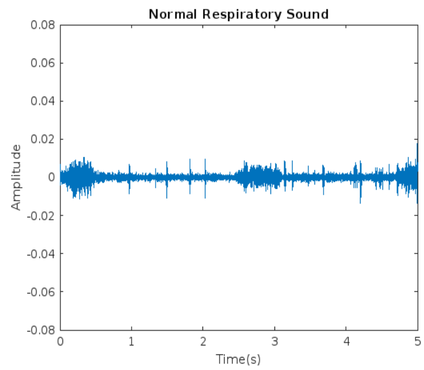

Figure 1. Time-amplitude plot for a normal respiratory sound

2.1.2. Bronchial Sounds

Bronchial sounds are high-pitched sounds that are usually heard over the large airways on the chest, in between the second and third intercostal space. They can be heard during both the inspiratory and expiratory phases. The intensity and time duration of the sound during the expiratory phase is normally longer than the inspiratory phase. It is also noticed that there is a short pause between consecutive breathing cycles [7].

2.1.3. Tracheal Sounds

Tracheal sounds are heard over the trachea and are usually loud and high-pitched. The frequency of tracheal sound varies from 100 to 5000 Hz [7]. As compared to normal lung sounds, the tracheal sound has a wider frequency range with a sharp drop in energy at a frequency of 800 Hz [8]. Listening to tracheal sounds is not a routine procedure, but it can be beneficial in understanding bronchial breath sounds and detecting upper airway obstruction.

2.1.4. Mouth Sounds

The central airways, which are influenced by turbulent airflow below the glottis, produce breath sounds that are audible from the mouth. The frequency range of breath sounds ranges from 200 to 2000 Hz [9]. In many cases, a normal person should not make any sounds from the mouth.

2.2. Adventitious Respiratory Sounds

The term "adventitious respiratory sound" describes unnatural sounds that are present in addition to regular breathing sounds. Adventitious respiratory sounds can be continuous or discontinuous. Continuous Adventitious respiratory Sounds (CAS) are abnormal and superimposed on normal respiratory sounds for more than 250 msec in one respiratory cycle.

Discontinuous respiratory sounds, on the other hand, are superimposed on normal breath sounds for a short period of time, typically less than 25 msec in one respiratory cycle.

2.2.1. Wheeze and Rhonchi

Both wheeze and rhonchi are CAS. Rhonchi is low-pitched, whereas wheeze is high-pitched. While the thickening of mucus in the bigger airways can induce rhonchi, the narrowing of the airways is typically what causes wheeze sounds. Wheeze and rhonchi both exhibit sinusoidal-like signals with frequencies ranging from 100 to 1000 Hz. Rhonchi is a low-pitched continuous sound with a prominent frequency of no more than 200 Hz, whereas wheeze is defined as a high-pitched continuous sound with a minimum of 400 Hz. Asthma, COPD, and the presence of a tumor can lead to the generation of wheeze, whereas bronchitis and COPD can result in the generation of rhonchi [9]. Time-amplitude plot for the wheeze respiratory sound is shown in Figure 2.

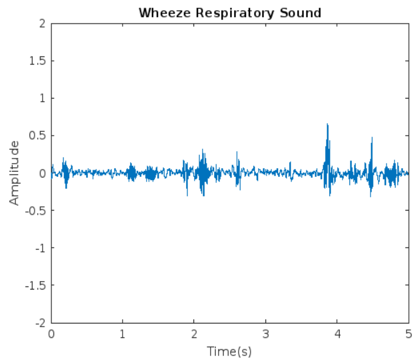

Figure 2. Time-amplitude plot for wheeze respiratory sound

2.2.2. Stridor

The presence of high-pitched CAS with a frequency greater than 500 Hz and duration greater than 250 msec is what defines stridor. The factors that contribute to stridor are turbulent airflow in the larynx and bronchial tree. Stridor is a sign of conditions such as laryngeal oedema, croup, and epiglottitis [9].

2.2.3. Squawk

During the inspiratory stage of the respiratory cycle, squawks can be clearly heard. Squawk is caused by oscillations in the peripheral airways. They are also known as short wheezes because of their low pitch and brief duration. Squawk typically has a frequency of 200 to 300 Hz. Presence of squawk is an indication of pneumonia [9].

2.2.4. Crackle

Crackle is a Discontinuous Adventitious respiratory Sound (DAS). They can also be divided into two categories: coarse crackle and fine crackle. Low-pitched coarse crackles with a frequency of about 350 Hz and duration of about 15 msec are well recognized. High-pitched fine crackles have a frequency of about 650 Hz and short duration of only 5 msec. Crackles may develop as a result of chronic bronchitis, bronchiectasis pneumonia, congestive heart failure, and lung fibrosis [9]. Time-amplitude plot for the crackle respiratory sound is shown in Figure 3.

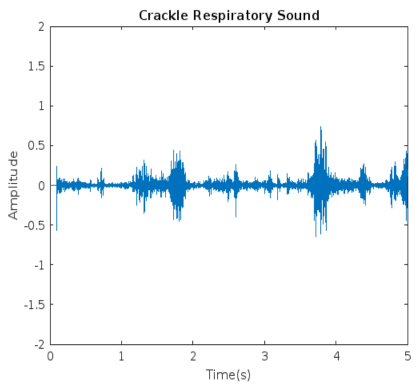

Figure 3. Time-amplitude plot for crackle respiratory sound

2.2.5. Pleural Rubs

A low-pitched DAS with a frequency of about 350 Hz and duration of less than 15 msec is called pleural rub. Rubs are caused by the pleural membranes rubbing against one another when breathing. They are brought on by pleural membrane inflammation, while pleural tumors may also contribute to their development [9].

Table 1 highlights the characteristics of normal and adventitious respiratory sounds [9, 10].

3. Dataset available for Respiratory Sounds

A central problem in the development of computerized respiratory sound analysis is the availability of public databases that can help researchers to develop algorithms and differentiate results. As shown in Table 2, Pramono *et al.* (2017) highlighted 13 publicly available databases used by several researchers. The database, which has attracted many researchers, is the R.A.L.E repository and audio CD from Understanding Lung Sounds 3rd edition [11]. The only constraint with these databases is the limited number of samples available for each respiratory sound.

At the 2017 International Conference on Biomedical and Health Informatics (ICBHI), two independent research teams from Portugal and Greece collected and created a database of various respiratory sounds, which was an impressive accomplishment. The database is made up of 5.5 hours of recordings made from 126 patients and contains 6898 respiratory cycles, of which 1864 have wheezes, 886 have crackles, and 506 have both. Many researchers in respiratory sound analysis view this database as a gold standard [3].

Researchers who aim to collect their own recordings will have to design an instrumentation system. Here the respiratory sounds are recorded either by electret microphones or sensitive accelerometers. This will be followed by suitable amplifiers and filters in the bandwidth of 50–2500 Hz. This data can be digitized at a sampling rate greater than 5kHz and acquired using a Data Acquisition system (DAQ). The factors that need to be considered here are the cut-off frequencies of the associated filters, the sensitivity of the sensors selected, the effective output voltage of the amplifier to be matched with the input range of DAQ, the impedance of the amplifier, and the sampling rate of DAQ [12].

Table 1. Characteristics of respiratory sounds [9][10]

Respiratory Sound	Continuous/ Discontinuous	Frequency (Hz)	Duration (ms)	Cause	Disease
Normal	Continuous	150-1000	5000	Normal	NA
Wheeze	Continuous	>400	>250	Airway narrowing	Asthma, Pneumonia
Rhonchi	Continuous	<200	>250	Bronchial secretions	COPD, Bronchitis
Stridor	Continuous	>500	>250	Turbulent airflow	Epiglottitis, Foreign body
Squawk	Continuous	200-300	±200	Airway oscillations	Pneumonia
Coarse Crackle	Discontinuous	350	<30	Air bubble in large bronchi	Bronchitis, Bronchiectasis, COPD, Pneumonia,
Fine Crackle	Discontinuous	650	<10	Explosive openings of small airways	Congestive heart failure, Lung fibrosis
Pleural Rubs	Discontinuous	350	>15	Rubbing of pleural membranes	Membrane inflammation, Tumours

Table 2. List of available datasets for respiratory sounds [11]

Sr. No.	Database
1	Auscultation skills: Breath and heart Sounds, 4th edition
2	East Tennessee State University repository
3	Fundamentals of lung and heart sounds
4	Heart and lung sounds reference library
5	Littmann repository
6	Lung sounds: An introduction to the interpretation of the auscultatory finding
7	R.A.L.E. repository
8	Secrets heart & lung sounds workshops
9	SoundCloud repository
10	The chest: Its signs and sounds
11	Understanding heart sounds and murmurs
12	Understanding lung sounds, the 2nd edition
13	Understanding lung sounds, the 3rd edition

4. Approaches for Respiratory Sound Analysis

Several approaches have been used for respiratory sound analysis. In a visual analysis of the respiratory sound signal, the signals are plotted in the form of a spectrogram. A spectrogram is a visual representation of the spectrum of frequencies of a signal as it varies with time. The resultant waveform is analyzed based on the frequency intensity of the signals. A well-trained physician can diagnose respiratory disorders based on the frequency intensity of the plotted signals. Again, this is a subjective way of analysis as it depends on the expertise of the physician. In Figure 4, the original sound signal and its spectrogram is shown [13].

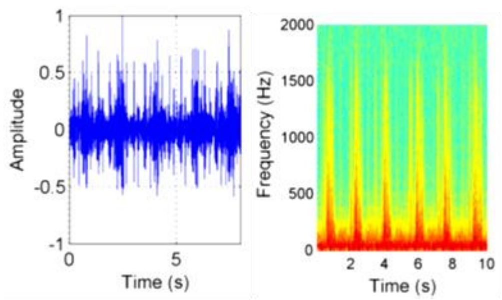

Figure 4. Visual representation of crackle respiratory sound (times vs amplitude) and its spectrogram (time vs. frequency) [13]

Chowdhary *et al.* (1982) developed a simple solution for the frequency analysis of adventitious respiratory sounds. The system consists of an instrumentation system consisting of a contact microphone to pick up respiratory sounds, amplified and filtered for the removal of any 50 Hz noise. Since the frequency of respiratory sounds extends up to 2000 Hz, several bandpasses filters were designed with different center frequencies (400, 800, 1200, and 2000 Hz) up to 2000 Hz. Wheeze, rales, and pleural friction rub were identified based on frequency-amplitude characteristics of the respiratory sounds. The plot of frequency vs. amplitude is shown in Figure 5 for the inspiratory and the expiratory phases [14].

Figure 5 shows that wheeze has higher high-frequency components than rales and rubs. The peak-to-peak amplitude of the wheeze is constant during the expiration phase up to 1200 Hz, after which it uniformly drops. The peak-to-peak amplitude of the wheeze drops unevenly during the inspiration phase. In the case of rubs during the inspiration phase, the peak-to-peak amplitude decreases and during expiration, it fluctuates with frequency. This work is simple but very objective in nature and may not be conclusive in classifying different respiratory sounds.

Polat *et al.*(2004) developed a computer-based method for collecting and analyzing respiratory sounds. The sole components of the system are a portable computer, some basic electronic components, and the software. Here respiratory sounds can be captured, saved, played again, and subjected to time- and frequency-domain analysis by the system. The device is a straightforward and practical instrument for measuring and analyzing respiratory sounds. The important feature of this system is that it gives provision to display both time-amplitude and spectral plot using fast Fourier transform (FFT). Zooming in on time series graphs allows for more in-depth views of some of the key areas of the plot [15].

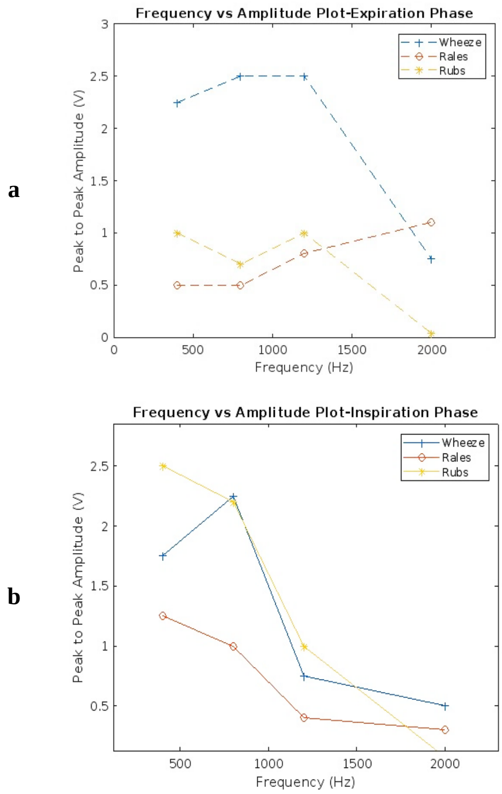

Figure 5. Frequency vs Amplitude plot of adventitious lung sounds. (a) expiration phase (b) inspiration phase

The spectrogram produced in this study presents an audible representation of respiratory sounds in visual form. The colors of the spectrogram at any moment show the relative intensity of the sound at that time and frequency. High-intensity respiratory sounds are displayed higher on the display, with the horizontal dimension representing time and the vertical dimension representing frequency. Furthermore, FFT methods are used to depict the Power Spectral Density (PSD). The respiratory sounds maximum frequency and median frequency over extended periods of time can be used to describe their frequency patterns [15].

S. Lev *et al.* (2010), I. Sanchez *et al.* (2003), S. Aydore *et al.* (2009), and I. Sen *et al.* (2010) have tried to use a statistical approach for the analysis of the respiratory sounds. In statistical analysis, datasets are processed to decide how frequently certain events occur based on their historical data. Some of the tests used in this statistical analysis include Analysis of Variance (ANOVA).

ANOVA is a statistical technique that is used to check if the means of two or more groups are significantly different from each other. Another method used in statistical analysis is Linear Discriminant Analysis (LDA). LDA is generally used to classify patterns between two classes [10].

Several researchers have also focused on the use of Machine Learning (ML) for automated respiratory sound analysis. Machine learning is a type of Artificial Intelligence (AI) that uses data and algorithms to imitate the way humans learn, ultimately improving the accuracy of the system. Researchers have focused on the use of machine learning algorithms such as Artificial Neural Networks (ANN), the Hidden Markov Model (HMM), k-nearest neighbor (k-nn) algorithm, Gaussian Mixture Model (GMM), Genetic Algorithms (GAs), and fuzzy logic.

In the classification of respiratory sounds, it is important to first extract desired features from the signal. R. Palaniappan *et al.* (2013) have mentioned these features can be extracted using time domain, frequency domain, and time-frequency domain analysis. The feature extraction techniques include the Autoregressive (AR) model, the Mel-Frequency Cepstral Coefficient (MFCC), energy, entropy, spectral features, and wavelet [16].

The numerous machine-learning techniques utilized by earlier researchers are mentioned in Table 3. Each method's accuracy is specifically mentioned. A variety of methods, including ANN, k-nn, HMM, GMM, fuzzy logic, and GA are used in automated respiratory sound analysis. ANN and k-nn are the techniques that are most frequently used. A. Kandaswamy *et al.* (2003) applied ANN to categorize wheeze, crackle, squawk, stridor rhonchus, and normal respiratory sounds. He reported an overall accuracy of 100% for training and 94.02% for testing [17].

S. Alsmadia *et al.* (2007), used k-nn to classify respiratory sounds in real time and reported an overall accuracy of 96% [18]. It has been observed that ANN and k-nn are quite good at classifying respiratory sounds. k-nn is fairly simple and reliable in its execution, and ANN can adapt to complex non-linear data quite well.

Table 3. Machine learning approach for respiratory sound analysis [16]

Sr. No.	Identified respiratory sounds	Method used	Classification accuracy
1	Normal respiratory sounds	k-nn and quadratic classifier	93.75% and 87.50% respectively
2	Wheeze and normal	ANN	Training set 1-93% and training set 2-96%
3	Normal and pathological	k-nn	Overall accuracy-69.59%
4	Normal, wheeze and crackles	ANN	Classification accuracy-95%
5	Airway obstructions	k-nn	60% to 90%
6	Normal and pathological	ANN	73%
7	Normal and pathological	k-nn	Encouraging results were reported
8	Wheeze and non-wheeze	Vector quantification	75.8% and 77.5% respectively
9	Normal and pathological	Nearest mean classifier	Satisfactory results
10	Normal and wheeze	GMM	Better accuracy as compared to vector quantification
11	Normal, wheeze, crackle, squawk, stridor and rhonchus	ANN	Training set A-100% and training set B-94.02%
12	Normal respiratory sounds	ANN	97.8%
13	Normal respiratory sounds	k-nn	Satisfactory
14	Normal, wheeze and crackle	ANN	81%-91%
15	Normal and abnormal	ANN	87.68%
16	Wheeze	GMM	90%
17	Fine and coarse crackles	GMM	95.1%
18	Normal respiratory sounds	k-means clustering	Precession of 0.9711
19	Normal and abnormal sounds	k-nn and minimum distance classifier	96%
20	Normal and abnormal	HMM	19.1% better than previous methods
21	Normal sounds	GMM	Sensitivity and specificity reported as 94.6% and 91.9% respectively.
22	Adventitious respiratory sounds	ANN	Improved results as compared to conventional neural network models.
23	Wheeze	ANN	92.86%
24	Normal and adventitious	ANN	92.36%
25	Normal, crackles and wheeze	GMM	98.75%
26	Normal, wheeze and crackles	ANN	Confidence levels of 0.90, 0.87 and 0.89 were reported respectively.
27	Asthma	Fuzzy logic	Satisfactory results
28	Normal respiratory sounds	k-means clustering	98.2% and 95.5% for tracheal recordings and ambient microphone respectively.
29	Normal and abnormal respiratory sounds	ANN	75% and 93% for healthy subjects and patients respectively.
30	Normal and pulmonary emphysema	HMM	87.4% to 88.7%
31	Healthy and pathological	k-nn	92.4±2.9%
32	Crackles	SVM	97.20%
33	Pneumonia and congestive heart failure (CHF)	SVM	86% and 82% was reported for pneumonia and CHF respectively.
34	Normal and abnormal	Empirical classification	98.34%

5. Discussion

5.1. Estimating PSD Using the Welch Method

M. Ariful *et al.* (2018) demonstrated the use of PSD for estimating four statistical features namely Mean of the absolute value (MABP), Variance (VAR), Kurtosis (KURT), and Skewness (SKEW). Here the PSD is estimated from the lung sound using Welch's method with a 1s window for better frequency resolution. Hanning window was applied here as it smoothens with an acceptable spectral leakage [19]. It is noteworthy to mention due to natural variations in the respiratory depth and frequency of respiration, the airflow level tends to change from subject to subject. Thus, the volume of the airflow decides the calculated power of the lung sounds.

5.2. Analyzing spectral characteristics of respiratory sounds using FFT

G. Furman *et al.* (2022) developed a system based on the analysis of FFT spectra of respiratory sounds. There is a specific change observed in the FFT spectra of respiratory sounds in the frequency range from 100 Hz to 2500 Hz [20]. This change in the spectra signifies the presence of lung diseases such as asthma, COPD, and pneumonia. For the diagnosis of Coronavirus disease 2019 (COVID-19), the frequency range from 2000 Hz to 6000 Hz is substantial. When the FFT spectra of the healthy volunteer and the COVID-19 patients are compared, the maxima and minima are located at several frequency ranges, as shown in Figure 6. It can be seen from the spectrum of the healthy patient that there exists a minimum at 2300 Hz and 4100 Hz, a maximum at 3100 Hz and 4900 Hz, and no extremum above 5300 Hz. Similarly, for a COVID-19 patient, there exists a minimum at 3300 Hz and 500 Hz, a maximum at 3900 Hz and 5600 Hz, and no extremum in the frequency range of 2300 Hz [20].

A test criterion is applied by calculating the ratios of the integrals of the harmonic amplitudes over several frequency ranges to classify healthy and ill patients. The harmonic amplitude is calculated by Equation 1.

$$I(f_a) = \int_{f_a-\Delta f}^{f_a+\Delta f} A(f)df \tag{1}$$

where f_a is the frequency of the extremum, A(f) if the harmonic amplitude at frequency f, Δf is half of the frequency range [20].

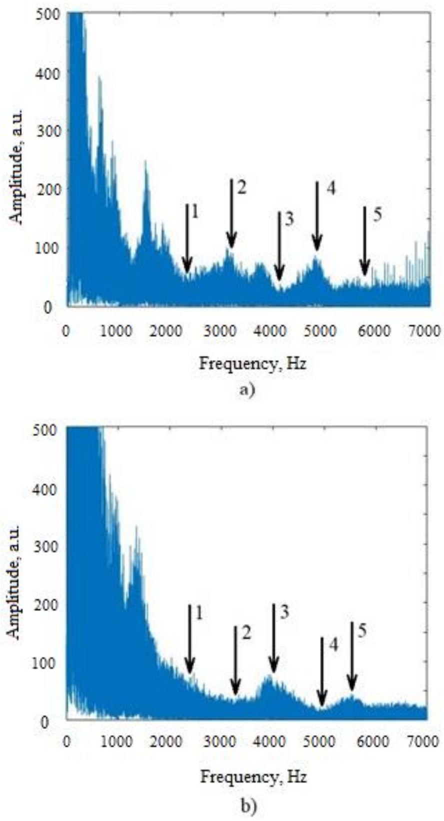

Figure 6. FFT spectra for a healthy volunteer and a COVID-19 patient [20]

5.3. Clinical Applications of Respiratory Sound Analysis

Respiratory sound analysis is a promising approach to diagnose several upper and lower airway diseases. For instance, we can use this technique in the diagnosis of asthma, bronchiolitis, obstructive sleep apnea, and in the evaluation of regional tissue ventilation. The site of the upper airway obstruction can be located during analysis, and the effectiveness of the therapy given can be assessed.

Spirometry will continue to be the gold standard in determining lower airway flow obstruction, but the process is slightly difficult to perform in the case of younger patients. Here, respiratory sound analysis can help us to assess younger patients. In younger children characterizing wheezing sounds can help us to learn more about both acute and chronic lower airway conditions. Monitoring regional ventilation and lung water content in patients who are intubated can be done with the use of multisite recording and analysis of respiratory sounds in critical care.

Wheeze severity in relation to flow obstruction has been expressed through the quantification of wheeze over time. The amount of the breath cycle taken up by wheezing (T_w/T_{tot}) in adult asthmatics with moderate to severe flow obstruction was inversely correlated with the Forced Expiratory Volume 1 (FEV1). Nocturnal asthma refers to asthmatic attacks that occur at night. It severely impairs lung function, increases symptoms, and requires medication. Noninvasive monitoring of respiratory sounds can help us quantify nocturnal asthma.

In patients with significant airway obstruction, the respiratory sound patterns frequently exhibit early crackles. Early crackles often are sparse, detectable at the mouth, and independent of gravity. The presence of late crackles is a sign of bronchiectasis and restrictive lung disease. Further analysis of fine and coarse crackles reveals their diagnostic significance in the identification of several respiratory disorders. Patients with fibrotic lung disorders, for instance, display fine crackles that last for a short duration, whereas patients with pneumonia display coarse crackles.

Although cough and snoring are not respiratory sounds, they have also been studied to identify differences in normal cough, the effect of asthma, and the effect of acute and chronic bronchitis on cough. Snoring, on the other hand, can also help us quantify obstructive sleep apnea or simple snoring [21].

6. Conclusion

Lung auscultation has been the mainstream for the diagnosis of several respiratory diseases and to check the patient's well-being. The early discovery of the stethoscope in 1800 changed the way doctors listened to heart and lung sounds. Since then, the stethoscope has been the gold standard. But because of the subjective nature of the stethoscope, several researchers are now focusing on the use of a digital or electronic stethoscope that also gives them the possibility to analyze and characterize features of respiratory sounds. It is easy to classify normal and adventitious respiratory sounds using computerized respiratory sound analysis. Further, using spectral analysis tools like FFT can help us to identify the type of respiratory sound, and by extracting features, it can easily help us to correlate the sounds with specific respiratory disorders. Today, it is possible to develop machine learning models that can aid in the automated and early detection of a number of respiratory disorders; the only concern is the availability of large datasets of respiratory sounds. For computer-based respiratory sound analysis to become a routine practice, there are certain technological challenges to be met. The development of low-cost sensors for recording respiratory sounds and developing techniques and algorithms to reject ambient and biological noise need to be addressed. Not only for the diagnosis of disease, but computer-based respiratory sound analysis can also help medical doctors and technicians for teaching and training purposes. A further computer-based approach will never replace a doctor, but it will help as a support mechanism in making proper decisions for disease diagnosis and planning the treatment plan.

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