Time-frequency Analysis of Normal and Abnormal Lung Breath Sounds with Short-time Fourier

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***Abstract*—This paper uses a short-time Fourier transform process to minimize errors in determining the type of breath sound through hearing. This process aims to visually determine the distribution of the respiratory sound frequency and the frequency distribution of the inspiration-expiration process. This study uses data on normal and abnormal breath sounds from Medzcool and hospitals in Lombok. The results of the spectrogram of normal breath sounds show that the frequency is distributed at 30 Hz – 1000 Hz, while the abnormal frequency is 100 Hz – 700 Hz. The process of inspiration-expiration in normal breathing is 12-20 times per minute. Abnormal breathing has a process that is less than 12 times per minute and more than 20 times per minute.**

Keywords—spectrogram, breath sound, frequency, short-time Fourier transform

I. INTRODUCTION

Breathing is inhaling oxygen in the air, known as the inspiration process, and removing carbon dioxide from the body, known as the expiration process [1]. The need for sufficient oxygen is essential so that humans can still maintain metabolism in the body. Lack of oxygen in the body can cause health problems and even death. One way to know normal or abnormal human breathing is the sound of the breath itself. These sounds occur during the process of inspiration and expiration. The sounds that occur due to these two processes can be heard by auscultation using a stethoscope. These processes can produce sounds that vary because it depends on which part of the respiratory system is affected. From Laënnec's era [2] until nowadays, auscultation has been adopted by physicians as an easy, fast and non-invasive way to evaluate and diagnose patients with lung diseases.

Nevertheless, auscultation exhibits noticeable drawbacks, as it suffers from subjectivity and variability in interpreting its diagnostic information. This diagnostic value can be better revealed when sound signal digitization and processing techniques are employed [3], [4]. In that way, novel diagnostic tools that objectively track the characteristics of the relevant pathology and assist the clinician in everyday practice could be introduced [5]. Assessment of the different types of sounds produced when breathing is very important for medical personnel. The goal is that medical personnel can assess whether the breathing sound is in the normal or abnormal category to take appropriate action.

Normal breath sounds are classified as tracheal, bronchial, vesicular, or bronchovesicular. Tracheal and bronchial sounds, produced by turbulent airflow, are loud and can be heard throughout inspiration and expiration over the trachea and mainstem bronchi. Vesicular breath sounds are faint; they are best heard over other chest wall areas throughout inspiration and at the beginning of expiration. Bronchovesicular breath sounds are heard over areas between the mainstem bronchi and the smaller airways; their pitch and duration are midway between those of tracheal and mainstem bronchi breath sounds and normal breath sounds heard over other chest wall areas [6].

There are two types of abnormal breath sounds, namely intermittent sounds and continuous sounds. Intermittent sounds include rhonchi (basic and dry) and pleural friction rub. Continuous sounds include wheezing and stridor. Ronchi is a sound produced through the airways because it contains a secret/exudate. In other words, the respiratory tract is constricted. In comparison, the pleural friction rub is a sound that occurs during the inspiration process due to a shift between the parietal pleura and the visceral pleura. Wheezing in respiratory sounds is the most specific asthmatic symptom [7]. Asthma is a disease of the respiratory tract. The disease can cause increased hyperresponsiveness of the respiratory tract. Increased hyperresponsiveness can produce a wheezing sound. Sound is one of the characteristics of asthmatics [8]. In comparison, stridor is a rough (hoarse) sound with a high or low pitch. The sound arises from each inhalation or exhalation. The cause is due to the narrowing (obstruction) of some of the upper respiratory tract [8].

Research related to diagnosing respiratory diseases such as lung and asthma has been done before. Research related to the disease has proven its success in diagnosing the disease based on the analysis of respiratory sounds. Sound analysis of the disease uses classification techniques such as a semi-supervised deep learning algorithm [9]; Convolutional neural networks [10]; biomimetic multi-resolution [11]; Time-frequency (TF) technique as well as wavelet packet decomposition (WPD) [12]; Support Vector Machine [13], [14]; multilayer perceptron (MLP) neural network and mel-frequency cepstral coefficients (MFCC) [15]; artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) [16]; and K-Nearest Neighbor Classification [17].

In this paper, the researchers conducted a short-time Fourier transform process. It aims to visually determine the distribution of respiratory sound frequencies, sound patterns, and the period of inspiration expiration. Describing the frequency distribution of the sound can be a recommendation for medical personnel to determine the patient's normal or abnormal breathing sounds being examined.

In the post-covid pandemic era, viruses that cause respiratory problems are often a frightening symptom. Therefore, medical personnel require rapid treatment to detect the patient's respiratory condition. The method of a short-time Fourier transform process can assist medical personnel in making decisions by visual observation.

II. METHOD

Short-time Fourier transform (STFT) is suitable for a band-limited signals like speech and sound. Mathematically, the STFT is modelled on (1) [18], [19].

$$STFT(\tau,f) = \int x(t)g(t-\tau)e^{-2\pi ft}dt \quad (1)$$

The working step of the short time-frequency Fourier transform is to divide the signal into small segments using a sliding window function $g(t)$ centred on τ. The Fourier transform is performed in a time localized manner on the signal $x(t)$ for each segment sequentially. The aim is to obtain information from the content of frequency variations over time [20].

Bicubic interpolation uses 4 x 4 of the neighbouring pixels to get information. The formula is modelled on (2) [21].

$$p(x,y) = \sum_{i=0}^{N-1}\sum_{i=0}^{N-1} a_{ij}x^i y^j \quad (2)$$

with
a = the location of the nearest neighbour pixel
x= the location of the new pixel horizontally
y= the location of the new pixel vertically

The breath sound data used in this paper was sourced from Medzcool. Medzcool is an interactive medical sound library to help you learn the physical exam skills of auscultation and patient medical records at a hospital in Lombok. Data varies from 10 to 16 seconds with a sampling frequency of 44,100 Hz. Normal breath sounds consist of trachea, bronchial, bronchovesicular, and vesicular. In contrast, abnormal respiratory sounds consist of rhonchi, pleural friction rub, wheezing, and stridor.

Respiratory data is processed using a short-time Fourier transform. The steps are as follows:

1. The windowing process is carried out on the breath sound signal with the same width,
2. The Fourier transform process is carried out on each segment from the windowing process to obtain the frequency content of each segment,
3. The process of calculating the power spectral density (PSD) is carried out,
4. The process of drawing the spectrogram is carried out where the x component shows the time, the y component shows the frequency, and the z component shows the power spectral densities,
5. The process of applying bicubic interpolation is carried out

III. RESULT AND DISCUSSION

A. *Normal Breathing Sounds*

The normal respiratory sound signals used and generated by the spectrogram are shown in Fig. 1 – Fig. 4. Based on the results of the spectrogram, it can be seen visually the distribution of respiratory tone frequency, power spectral density and the period of inspiration-expiration (breathing period), and the frequency of the inspiration-expiration process in time per minute as shown in Table I.

TABLE I. NORMAL BREATHING SOUNDS

Type of Breathing Sounds	**Pitch frequency distribution**	**Power spectral density**	**Breathing period**	**Inspiration-expiration process**
	(Hz)	**(dB/Hz)**	**(s)**	**Time/ minute**
Tracheal breath sounds	30-600	-40	4	15
Bronchial breath sounds	100-800	-40	3	20
Bronchovesicular breath sounds	200-1000	-40	3	20
Vesicular breath sounds	100-700	-40	3.5	17

The four normal breathing patterns in the spectrogram can be explained as follows:

a. Tracheal breath sounds
The spectrogram is shown in Fig. 1(b). Pitch is spread at a frequency of 30-600 Hz. Fig. 1(b) indicates a red power spectral density of about -40 dB/Hz. Pitch looks longer and louder in the expiration than in the inspiration with a breathing period of about 4 seconds, so 1 minute occurs 15 times for the inspiration-expiration process.

b. Bronchial breath sounds
The spectrogram is shown in Fig. 2(b). Pitch is spread at a frequency of 100-800 Hz. This is indicated by a red spectral density of about -40dB/Hz. The pitch produced during the process of inspiration and expiration looks loud. However, the pitch appears shorter during expiration. The time of inspiration and expiration is almost the same as the period of breathing which is about 3 seconds, so one minute occurs 20 times for the inspiration-expiration process.

c. Bronchovesicular breath sounds
The spectrogram is shown in Fig. 3(b). The pitch is spread in the 200-1000 Hz frequency, which is indicated by the red spectral density of about -40dB/Hz. The time used for the process of inspiration and expiration is almost the same as the breathing period, which is about 3 seconds. As a result, one minute occurs 20 times the inspiration-expiration process.

d. Vesicular breath sounds
The spectrogram is shown in Fig. 4(b). The pitch is spread at a 100 - 700 Hz frequency, marked by a red spectral density of about -40 dB/Hz. The pitch produced on inspiration is more extended than expiration, which is a ratio of 3:1. The period of breath occurs in about 3.5 seconds, so in one minute, there is 17 times the inspiration-expiration process.

Based on spectrograms of the tracheal, bronchial, bronchovesicular, and vesicular breath sounds in Fig. 1- Fig. 4 obtained that normal breath sounds are distributed at a frequency of 30 Hz – 1000 Hz. The results of the analysis of normal breath sound from Fig. 1 - Fig. 4 are obtained from 15 times per minute to 20 times per minute, and this result follows the frequency of normal breath sounds for adults, which is in the range of 12 - 20 times per minute [6]-[23].

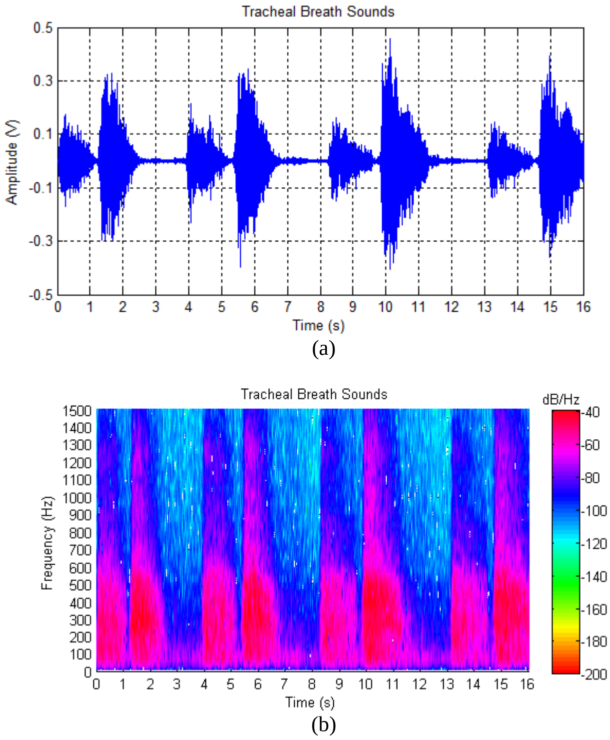


Fig. 1. Example of a figure caption Tracheal breath sounds – Normal lung sounds: (a) sounds signal and (b) spectrogram.

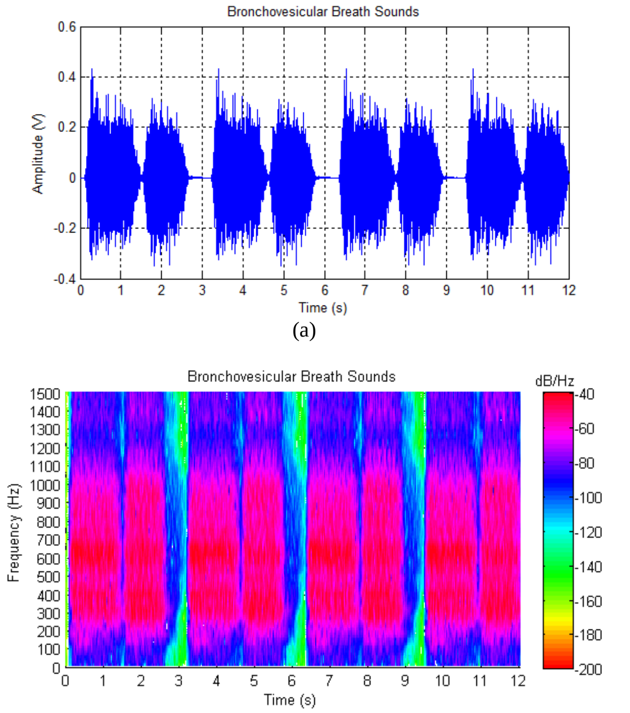


Fig. 3. Bronchovesicular breath sounds – Normal lung sounds: (a) sounds signal and (b) spectrogram.

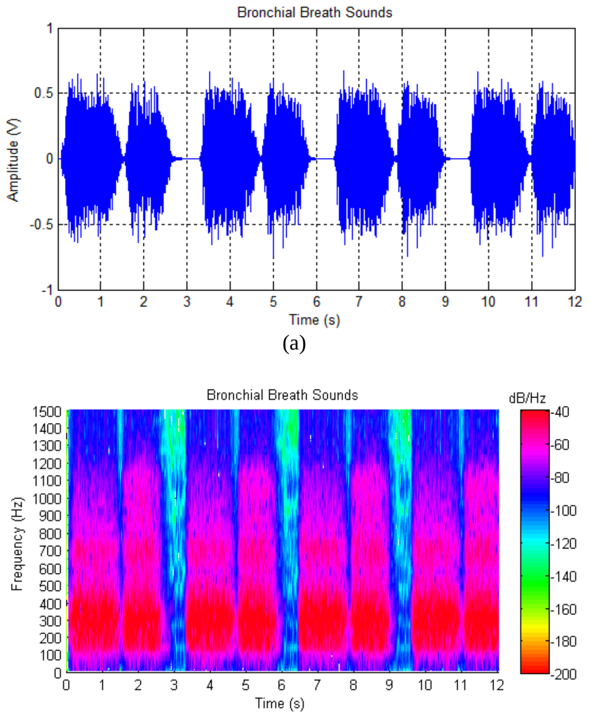


Fig. 2. Bronchial breath sounds – Normal lung sounds: (a) sounds signal and (b) spectrogram.

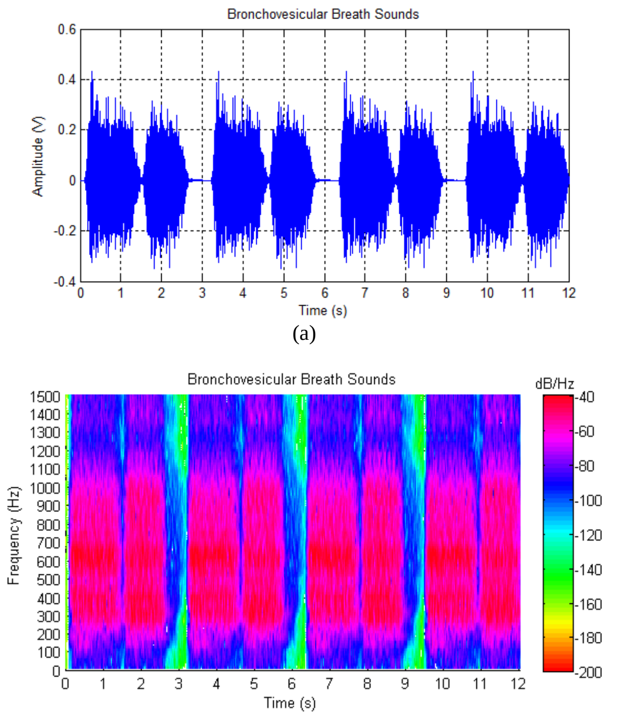


Fig. 4. Vesicular breath sounds – Normal lung sounds: (a) sound signal and (b) spectrogram

B. Abnormal Breathing Sounds

The abnormal respiratory sound signals used and generated by the spectrogram are shown in Fig. 5 – Fig. 8. Based on the results of the spectrogram, it can be seen visually the distribution of respiratory tone frequency, power spectral density and the period of inspiration-expiration (breathing period), and the frequency of the inspiration-expiration process in time per minute as shown in Table II.

The four abnormal breathing patterns in the spectrogram can be explained as follows:

a. Wheezing

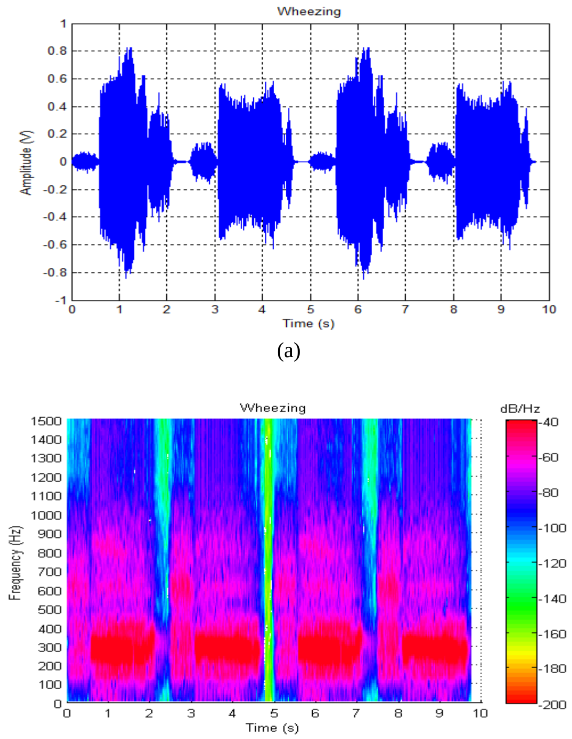
The spectrogram is in Fig. 5(b) shows that the pitch is distributed at a frequency of 200-400Hz. The red spectral density indicates this with a -40dB/Hz value. The duration of the pitch used on inspiration is approximately 0.5 seconds. In contrast, the duration used for expiration is 1.5 seconds. The means that these two processes have a duration ratio of 1:3. Based on the pitch of the sound of normal breathing, the average time used in the inspiration process is longer or equal to the time used in the expiration process. While the pitch of the wheezing sound, the time used for the expiration process is longer. In addition, during the process, it has a louder sound and is marked in red. The breathing period occurs in about 2.5 seconds. As a result, one minute occurs about 24 times the process of inspiration-expiration.

b. Stridor
The spectrogram in Fig. 6(b) shows that the pitch is spread at 100-700 Hz. This is indicated by the red spectral density of about -40dB/Hz. The duration of the inspiratory and expiratory pitches is about 1 second with a ratio of 1:1. The breathing period lasts about 1.5 seconds. As a result, one minute occurs about 40 times the process of inspiration-expiration.

c. Rhonchi
The spectrogram in Fig. 7(b) shows that the pitch is spread at a 200-700 Hz frequency. This is indicated by the red spectral density of about -40dB/Hz. The time spent on inspiratory and expiratory pitches is about 4.5 seconds. No pause occurs in the following inspiration-expiration process. The duration used in the inspiration process is shorter than the expiration process, with a time ratio of 1:3. The breathing period occurs in 4.5 seconds. As a result, one minute occurs 11 times the process of inspiration-expiration.

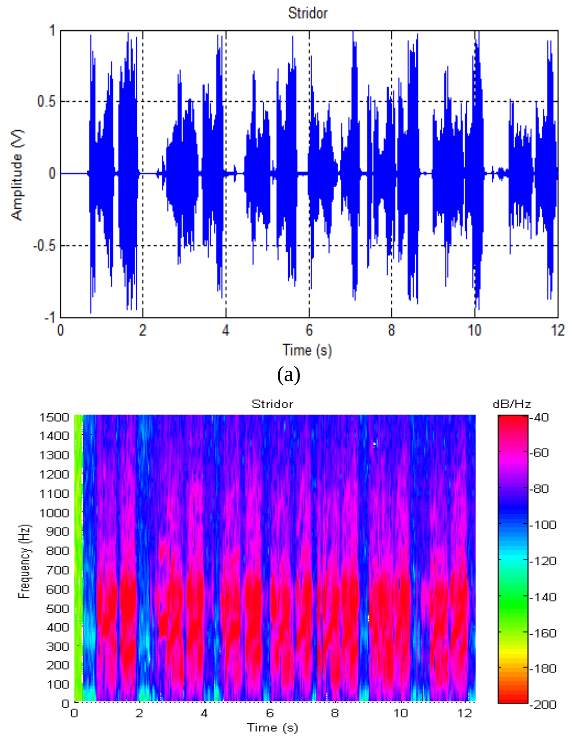
d. Pleural friction rub
The spectrogram in Fig. 8(b) shows that the pitch is spread at 100-400 Hz. This is indicated by the red spectral density, around -40dB/Hz. The time used for inspiratory and expiratory pitches is about 2 seconds. The duration that occurs during the inspiration process is longer than during the expiration process, with a time ratio of 2:1. The breathing period lasts about 2.8 seconds. Hence, one minute occurs about 21 times the inspiration-expiration process.

Based on the spectrogram of wheezing, stridor, rhonchi, and pleural friction rub in Fig. 5 - Fig. 8, abnormal breath sounds are distributed at 100 Hz - 700 Hz. The analysis of abnormabreathing sound results from Fig. 5- Fig. 8 obtained a respiratory frequency of fewer than 12 times per minute and greater than 20 times per minute. The corresponds to the abnormal respiratory frequency of adults outside the range of 12-20 breaths per minute [6]-[23].



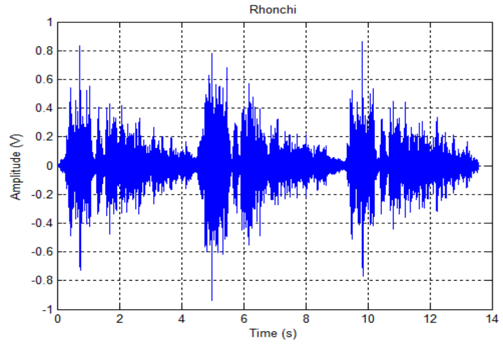
(b)

Fig. 5. Wheezing breath sounds – lung sounds: (a) sounds signal and (b) spectrogram

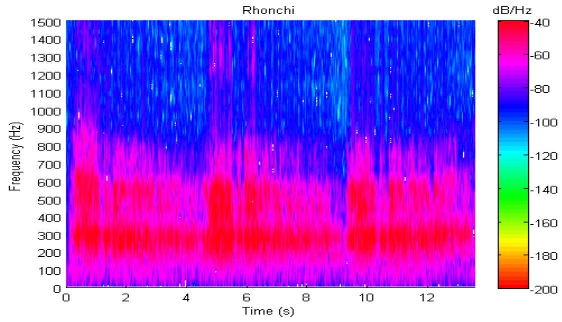


(b)

Fig. 6. Stridor breath sounds – lung sounds: (a) sounds signal and (b) spectrogram.

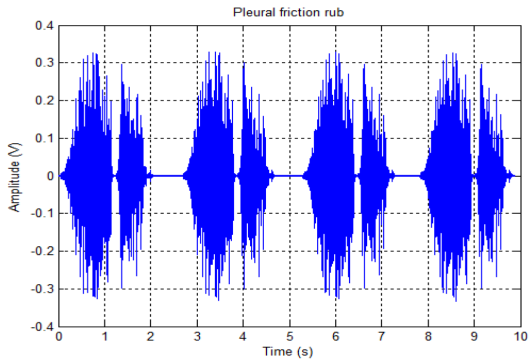


(a)



(b)

Fig. 7. Rhonchi breath sounds – lung sounds: (a) sounds signal and (b) spectrogram



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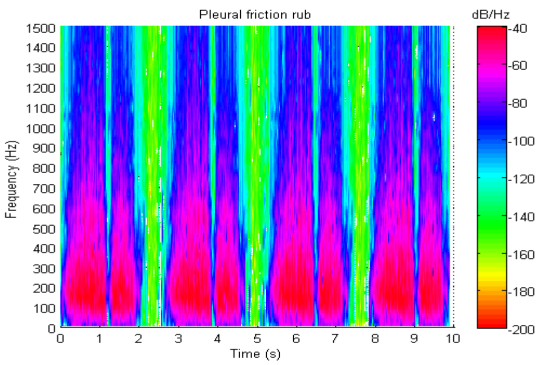


(b)

Fig. 8. Pleural friction rub – lung sounds: (a) sounds signal and (b) spectrogram

TABLE II. ABNORMAL BREATHING SOUNDS

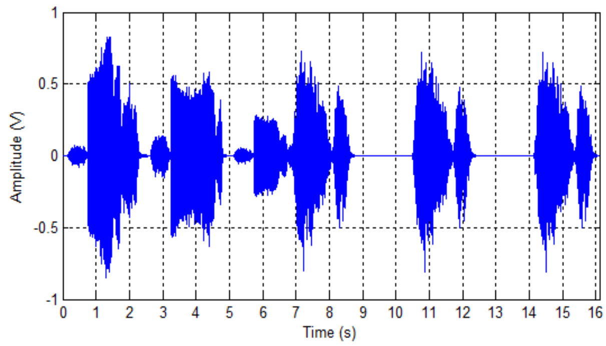
Type of Breathing Sounds	Pitch frequency distribution	Power spectral density	Breathing period	Inspiration -expiration process
	(Hz)	*(dB/Hz)*	*(s)*	*Time/minute*
Wheezing	200-400	-40	2.5	24
Stridor	100-700	-40	1.5	40
Rhonchi	200-700	-40	4.5	11
Pleural friction rub	100-400	-40	2.8	21

C. Breathing Sounds Test

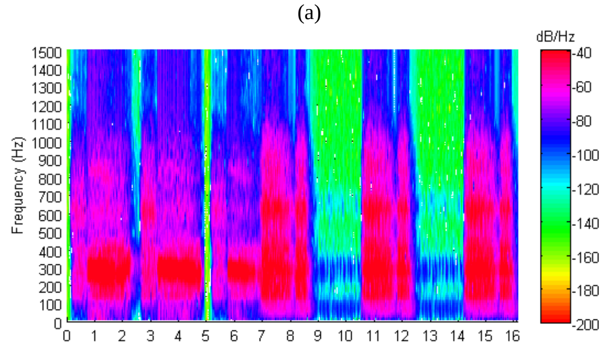
The breath sounds used for testing are breath sounds that have been determined by Medzcool and a doctor at the hospital. The data contains wheezing and vesicular breath sounds for data from Medzcool, while data from the hospital contains wheezing and rhonchi pitch.

Fig. 9 – Fig. 11 are test signals. These signals are compared with those in normal and abnormal sounds, as shown in Fig. 1 – Fig. 8. In Fig. 9, 3 pitch patterns resemble wheezing at the 1st to 7th second. In the figure, three normal breathing pitch patterns resemble vesicular breath sounds indicated in the 7th to the last second.

Fig. 10 shows a pattern of normal breathing pitch that resembles a vesicular breath sound for two seconds. In addition, in the figure, five patterns resemble wheezing pitch from the 2nd second to the last. As for Fig. 11, there is a wheezing pattern. The pattern occurs from 1st to 2nd, the 3.5th to 4.5th second, and the 9th to last. In addition to the pattern that occurred at that time, other patterns resemble Ronchi. The visual analysis results with a short-time Fourier transform show that the resulting pitch pattern corresponds to the type of data from Medzcool and the data that the hospital has determined.

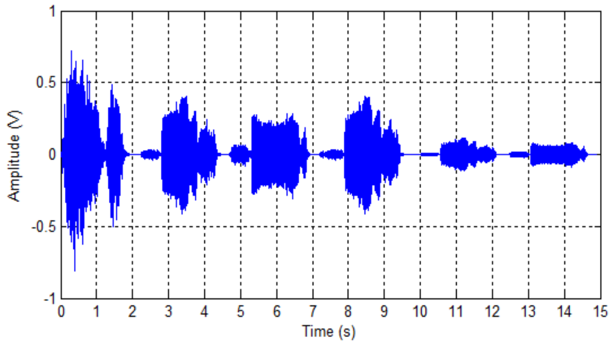


(a)

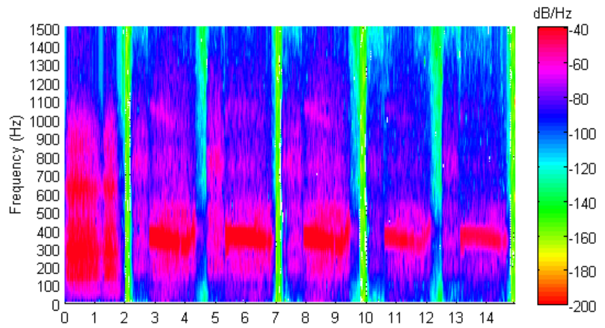


(b)

Fig. 9. 1st Test breath sounds: (a) sounds signal and (b) spectrogram.

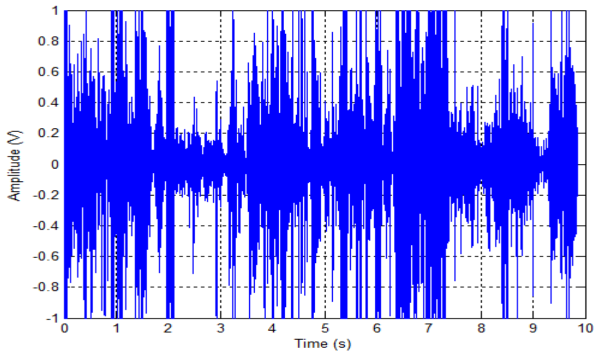


(a)

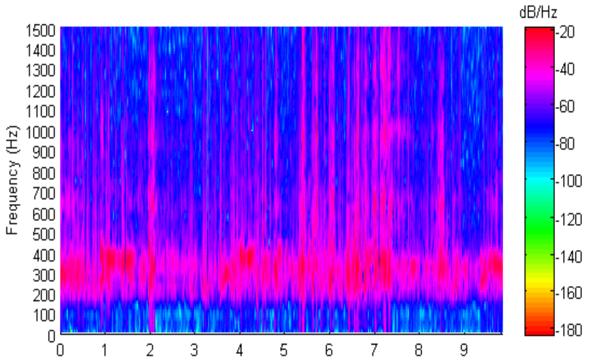


(b)

Fig. 10. 2nd Test breath sounds: (a) sounds signal and (b) spectrogram.



(a)



(b)

Fig. 11. 3rd Test breath sounds: (a) sounds signal and (b) spectrogram.

IV. CONCLUSIONS

The spectrogram in this paper shows that normal breath sounds are distributed at a frequency of 30 Hz – 1000 Hz. In contrast, abnormal breath sounds are distributed at 100 Hz - 700 Hz. The process of inspiration - expiration in normal breathing is in the range of 12-20 times per minute, i.e., 15 - 20 times per minute, whereas abnormal breathing is less than 12 times per minute and greater than 20 times per minute. Differences in the type of normal or abnormal sound can be seen from the frequency distribution pattern in the pitch of sound and length of the sound in the inspiration-expiration process.

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REFERENCES

[1] C. A. Del Negro, G. D. Funk, and J. L. Feldman, "Breathing matters," *Nat. Rev. Neurosci.*, vol. 19, no. 6, pp. 351-367., 2018.

[2] R. T. H. Laennec, "De l'auscultation médiate: ou traité du diagnostic des maladies des poumons et du coeur," in *2*, 1819.

[3] N. Avriely and W. C. David, *Breath sounds methodology*. CRC Press, 2019.

[4] L. J. Hadjileontiadis, Y. A. Tolias, and S. . Panas, "Intelligent system modeling of bioacoustic signals using advanced signal processing techniques," *Intell. Syst. Technol. Appl.*, vol. 3, pp. 103-156., 2002.

[5] S. A. Taplidou and J. H. Leontios, "Wheeze detection based on time-frequency analysis of breath sounds," *Comput. Biol. Med.*, vol. 37, no. 8, pp. 1073–1083, 2007.

[6] J. S. Coviello, *Auscultation skills: Breath & heart sounds: Fifth edition*. 2013.

[7] D. Oletic and B. Vedran, "Asthmatic wheeze detection from compressively sensed respiratory sound spectra," *IEEE J. Biomed. Heal. informatics*, vol. 22, no. 6, pp. 1406–1414, 2017.

[8] A. Satriadi, I. M. Budi Suksmadana, and B. Kanata, "Analisis Suara Pernapasan Paru-Paru Asma Dengan Tidak Asma Menggunakan Metode K Nearest Neighbors," *Dielektrika*, vol. 8, no. 1, p. 1, 2021, doi: 10.29303/dielektrika.v8i1.251.

[9] D. Chamberlain, K. Rahul, G. Daniela, M. Vivek, and R. F. Richard, "Application of semi-supervised deep learning to lung sound analysis," in *2016 38th Annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, 2016, pp. 804–807.

[10] F. Demir, S. Abdulkadir, and B. Varun, "Convolutional neural networks based efficient approach for classification of lung diseases," *ealth Inf. Sci. Syst.*, vol. 8, no. 1, 2020.

[11] D. Emmanouilidou, P. Kailash, W. James, and E. Mounya, "A multiresolution analysis for detection of abnormal lung sounds," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, pp. 3139–3142.

[12] S. Emrani and K. Hamid, "Wheeze detection and location using spectro-temporal analysis of lung sounds," in *2013 29th Southern Biomedical Engineering Conference*, 2013, pp. 37–38.

[13] S. Abbasi, D. Roya, A. Ataollah, and Y. Sarbaz, "Classification of normal and abnormal lung sounds using neural network and support vector machines," in *2013 21st Iranian Conference on Electrical Engineering (ICEE)*, 2013, pp. 1–4.

[14] F. Jin, S. Farook, and Y. G. Daniel, "New approaches for spectro-temporal feature extraction with applications to respiratory sound classification.," *Neurocomputing*, vol. 123, pp. 362–371, 2014.

[15] A. Hashemi, A. Hossein, and A. Khosrow, "Classification of wheeze sounds using cepstral analysis and neural networks," *Med. Meets Virtual Real.*, vol. 19, pp. 161–165, 2012.

[16] R. J. Oweis, E. W. Abdulhay, A. Khayal, and A. Awad, "An alternative respiratory sounds classification system utilizing artificial neural networks," *Biomed. J.*, vol. 38, no. 2, pp. 153–161, 2015, doi: 10.4103/2319-4170.137773.

[17] C. H. Chen, W. T. Huang, T. H. Tan, C. C. Chang, and Y. J. Chang, "Using K-nearest neighbor classification to diagnose abnormal lung sounds," *Sensors (Switzerland)*, vol. 15, no. 6, pp. 13132–13158, 2015, doi: 10.3390/s150613132.

[18] S. W. Kim and S. Y. Kim, "Analysis of dispersion of pulse signals in underground tunnels using finite-difference time domain and short-time fourier transform," *Proc. 13th Internarional Conf. Gr. Penetrating Radar, GPR 2010*, no. 1, 2010, doi:

10.1109/ICGPR.2010.5550216.

[19] Y. Li, W. Peng, X. Zhu, G. Wei, H. Yu, and G. Qian, “Based on short-time fourier transform impulse frequency response analysis in the application of the transformer winding deformation,” *2016 IEEE Int. Conf. Mechatronics Autom. IEEE ICMA 2016*, pp. 371–375, 2016, doi: 10.1109/ICMA.2016.7558591.

[20] R. X. Gao and R. Yan, “Non-stationary signal processing for bearing health monitoring,” *Int. J. Manuf. Res.*, vol. 1, no. 1, pp. 18–40, 2006, doi: 10.1504/IJMR.2006.010701.

[21] D. Abdullah, F. Fajriana, M. Maryana, L. Rosnita, A. P. U. Siahaan, R. Rahim, P. Harliana, H. Harmayani, Z. Ginting, C. I. Erliana, D. Irwansyah, Z. Zulmiardi, M. Khaddafi, F. Milanie, H. Aspan, I. Huda10, K. Saddhono, I. Mulyaningsih, R. M. Moonti, Parwito, H. Djanggih, A. Amalia, E. Winarno, and W. Hadikurniawati., “Application of Interpolation Image by using Bi-Cubic Algorithm,” in *Journal of Physics: Conference Series*, 2018, vol. 1114, no. 1. doi: 10.1088/1742-6596/1114/1/012066.

[22] M. Wulandari, “Index quality assesment citra terinterpolasi (SSIM dan FSIM),” *J. Terap. Teknol. Inf.*, vol. 1, no. 1, pp. 11–20, 2017, doi: 10.21460/jutei.2017.11.5.

[23] M. C. Huang, W. Xu, J. Liu, L. Samy, A. Vajid, N. Alshurafa, and M. Sarrafzadeh, “Inconspicuous on-bed respiratory rate monitoring,” 2013. doi: 10.1145/2504335.2504353.