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Lung Sound Classification Using Hjorth Descriptor Measurement on Wavelet Sub-bands

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Abstract

Signal complexity is one point of view to analyze the biological signal. It arises as a result of the physiological signal produced by biological systems. Signal complexity can be used as a method in extracting the feature for a biological signal to differentiate a pathological signal from a normal signal. In this research, Hjorth descriptors, one of the signal complexity measurement techniques, were measured on signal sub-band as the features for lung sounds classification. Lung sound signal was decomposed using two wavelet analyses: discrete wavelet transform (DWT) and wavelet packet decomposition (WPD). Meanwhile, multi-layer perceptron and N-fold cross-validation were used in the classification stage. Using DWT, the highest accuracy was obtained at 97.98%, while using WPD, the highest one was found at 98.99%. This result was found better than the multi-scale Hjorth descriptor as in previous studies.

Keywords

Activity, Complexity, Hjorth Descriptor, Lung Sound, Mobility, Wavelet Transform

1. Introduction

The lung sounds provide valuable information about the health condition of the lung. They have a typical pattern occurred by reason of the respiratory process. A disease or abnormality of the lung or respiratory tract will change the lung sound pattern [1]. Many researchers have attempted to develop a variety of methods to automatically perform the lung sounds classification. Wavelet transform is one method that is frequently used for physiological signals analysis [2].

Wavelet becomes popular in the biological signal processing in light of its simplicity in analyzing the signals in several different resolutions. In the study of lung sounds, wavelets were used to reduce the noise in the lung sounds [3], improve the quality of the lung sound [4], and extract the feature [5]. The use of wavelet in feature extraction is commonly performed to break down the lung sounds into several sub-bands before the calculation of some parameters on them. The most popular wavelet decomposition method is a discrete wavelet transform (DWT) level 7, which produces eight sub-bands [5–8]. The parameters calculated on sub-band include average power, mean absolute of wavelet coefficients, skewness, kurtosis, and energy comparison between adjacent sub-bands [7].

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Several studies showed that the majority of biological signals have a multi-scale nature [9]. Hence, the measurement of signal parameters in multi-scale can provide more information about the biological signals [10]. In the previous study, we conducted Hjorth descriptors measurements for the feature extraction of lung sounds [11], and it was found that Hjorth descriptor could generate the accuracy of 83.95% using activity, mobility, and complexity as features. In the next study, we measured Hjorth descriptor on a multi-scale scheme by means of the coarse-grained procedure as the multi-scale approach as conducted in [9]. Here, the best result showed the accuracy of 95.06% [12]. In other research, Hjorth descriptor was combined with empirical mode decomposition (EMD) for lung sound classification [13]. It then achieved the highest accuracy of 97.98% for five data classes. In [14], multidistance signal level difference (MSLD) method was proposed to generate a series of the new signal for Hjorth descriptor measurement. The method produced the accuracy of 97.98% using the same data in [12,13].

In this paper, the Hjorth descriptors measurement was performed on wavelet sub-band to improve accuracy. We used two wavelet decomposition scenarios, as proposed in [6,15]. We also examined the possibility of reducing the number of features used as well as generated high accuracy. Wavelet decomposition was proven as a powerful method to analyze a signal in a multi-resolution manner. By the combination of wavelet decomposition and Hjorth descriptor, it is expected that it could produce higher accuracy.

This paper is organized as follows: Section 2 discusses the materials and methods used in this research. Section 3 presents the results and discussion of Hjorth descriptor measurement on wavelet sub-band, and Section 4 provides the conclusion of the paper and some suggestions for future works.

2. Materials and Methods

As shown in Fig. 1, the method began by performing preprocessing on the lung sound, including the amplitude normalization and the DC component elimination. It continued to the wavelet decomposition applied to the signal using two schemes. The first scheme used DWT level 7 as described in [6] and the second one used WPD level 5, as described in [15]. The Hjorth descriptor was calculated on each sub-band to obtain the feature from the signal. Furthermore, classification was done using multi-layer perceptron (MLP) and N-fold cross-validation for validation. More detailed steps will be explained in the following subsections.

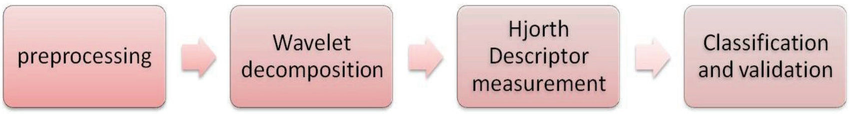


Fig. 1. Block diagram of the proposed system.

2.1 Lung Sound Data

The lung sound data consisted of five classes: normal, asthma, crackle, pleural rub, and stridor. Table 1 presents the number of each data category.

Data were collected from various sources such as from [16–19]. The lung sound data were cut into one respiration cycle and resampled with the sampling frequency of 8,000 Hz. Each data class had some different characteristics. Normal lung sound had a non-musical characteristic heard at inspiration and expiration phases. This sound indicated that the lung was in a healthy condition [1]. Wheeze sound was characterized by musical, high-pitched, continuous sound heard during inspiration, expiration, or both [1]. Crackle referred to an adventitious, non-musical, and explosive lung sound in a short duration and was divided into fine and coarse crackle [20]. The pleural rub referred to the lung sound associated with pleural inflammation or tumors in pleura [1], and stridor was wheeze sound with low frequencies frequently occurred in tracheal stenosis [20]. Fig. 2 displays the wheeze sound example and its spectrum.

Table 1. Lung sound data

Data class	Number of data
Normal	22
Wheeze	18
Crackle	21
Pleural rub	18
Stridor	20
Total	99

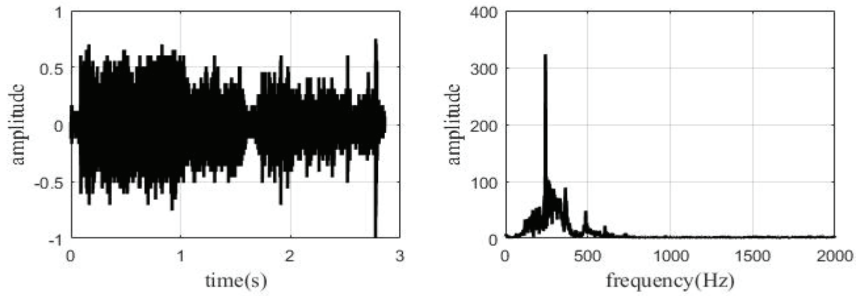


Fig. 2. Wheeze sound produced by asthma and its spectrum.

2.2 Wavelet Decomposition

2.2.1 Discrete wavelet transform

In general, the wavelet transform can be expressed as follows:

$$X(a,b) = \frac{1}{\sqrt{b}} \int_{-\infty}^{\infty} x(t)\Psi\left(\frac{t-a}{b}\right) dt \tag{1}$$

a denotes the time shift, b is the scale and $\Psi\ (t)$ is the mother wavelet [21]. Fig. 3 practically shows the procedure of the DWT. The signal is filtered in a pair of the filter (HPF and LPF) and then down-sampled with factor 2. The output of the HPF is called as the detail coefficients D1, while the output LPF is called as approximation coefficient A1. The output of LPF will be filtered further as the input signal to produce A2 and D2. The process continues until reaching the desired decomposition level.

In this study, we used 8,000 Hz as sampling frequency to produce a DWT order of 7 to provide A7, D7–D1 subbands, as shown in Fig. 4. Each level of DWT would generate half of its original bandwidth in view of the filtering process and down-sampling process. Hjorth descriptors were calculated for each sub-band that resulted in 24 features.

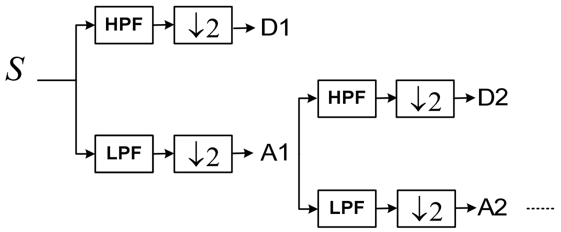


Fig. 3. DWT implementation.

A7	D7	D6	D5	D4	D3	D2	D1
0-31. 25 Hz	31.25-62.5 Hz	62.5-125 Hz	125-250 Hz	250-500 Hz	500-1000 Hz	1000-2000 Hz	2000-4000 Hz

Fig. 4. Sub-band frequency for DWT order 7.

2.2.2 Wavelet packet decomposition

On wavelet packet decomposition (WPT), decomposition was executed on the approximation coefficient and the detail coefficients as presented in Fig. 5.

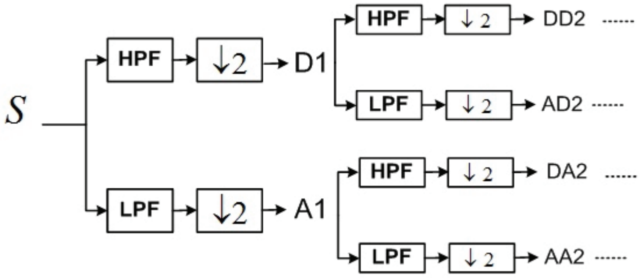


Fig. 5. WPD implementation.

In this research, WPD level 5 with sub-band was used for Hjorth descriptor calculation, as shown in Fig. 6. As there were 15 selected sub-bands, it would then produce 45 features [15].

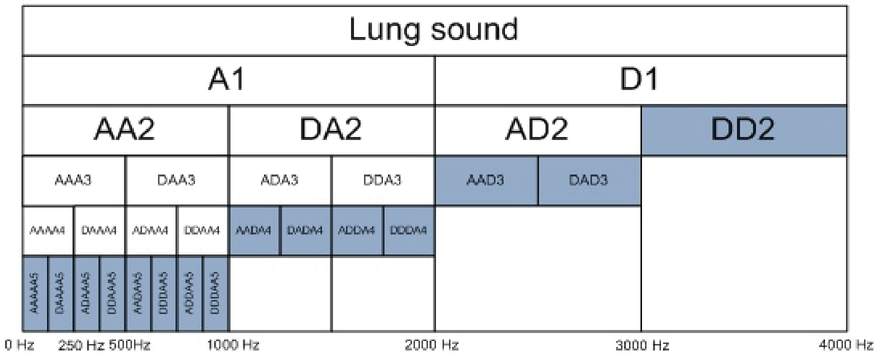


Fig. 6. Sub-band used in WPD scheme.

2.3 Hjorth Descriptor

Hjorth descriptor is a parameter to express the characteristics of biological signals [22]. It is also called the normalized shape descriptors (NSD) comprising three parameters: activity, mobility, and complexity [22,23]. Hjorth descriptors measure the low order spectrum moment through calculations in the time domain [24].

For an input signal $x(n)$, the first derivative of $x(n)$ was expressed as $x'(n) = x(n) - x(n-1)$, meanwhile, a second derivative of $x(n)$ was expressed as $x''(n) = x'(n) - x'(n-1)$. If σ was considered as the standard deviation of $x(n)$, the three parameters in the Hjorth descriptor would be expressed as:

$$Activity = {\sigma_x}^2 = \frac{\sum_{n=1}^{N-1}(x(n)-\bar{x})}{N} \quad (2)$$

$$Mobility = \frac{\sigma_{x\prime}}{\sigma_x} \quad (3)$$

$$Complexity = \frac{\sigma_{x''}/\sigma_{x\prime}}{\sigma_{x\prime}/\sigma_x} \quad (4)$$

2.4 Classification and Validation

MLP was used as a classifier. It has simplicity in computation and its performance can be adjusted by changing the number of hidden neurons. In the experiment, we evaluated the effect of hidden neuron number on the classification accuracy. We here used the N-fold cross-validation as a validation method. As we used $N = 3$, each data set would contain at least 6–8 for training data and testing data.

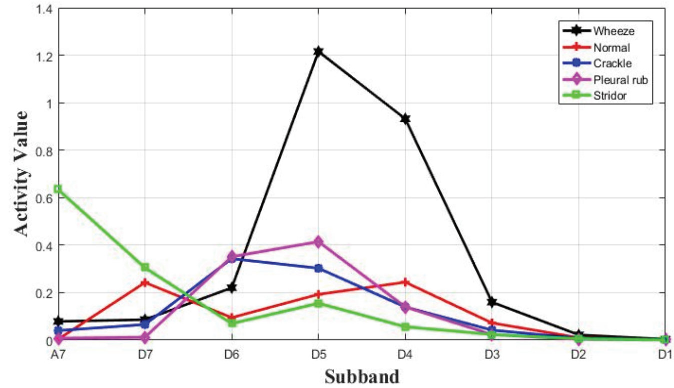
3. Results and Discussion

3.1 DWT Hjorth Descriptor

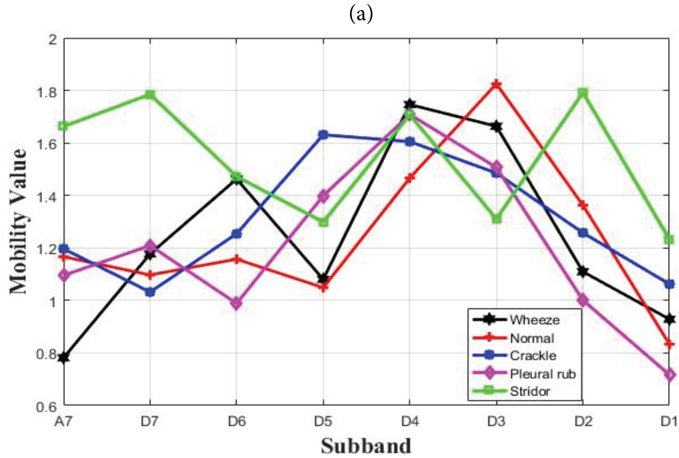
Fig. 7 shows the calculation result of each Hjorth descriptor on the sub-band of the DWT result. It has been found that the activities had a number of high values on sub-band A7, D2, and D1, except stridor. Mobility and complexity had a higher value on the three sub-bands. The stridor had a low value for complexity but high value for mobility. The Hjorth descriptor feature generated from this DWT process would be used as input from the MLP.

As previously explained, DWT produced 24 features using all Hjorth descriptor's parameters. We used MLP configuration with several hidden neuron's numbers: 15, 30, and 45. To see the effect of each feature on accuracy, we individually used Hjorth descriptor. The accuracy for each combination is shown in Table 2.

As shown in Table 2, the highest accuracy reached 97.98% obtained in the use of all features on the Bior1.5 wavelet and N-15-5 MLP configurations. Meanwhile, the mobility features reached 97.98% of accuracy using Bior1.5 wavelet on N-30-5 MLP configuration. The activity individually produced the highest accuracy at 93.94% using Db2 wavelet, while the complexity produced the highest accuracy of 96.97% using Bior1.5 wavelet.



(a)



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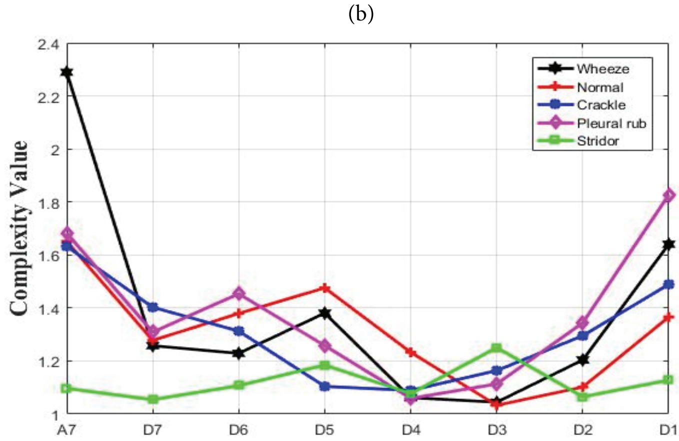


(c)

Fig. 7. Results of each sub-band and class of data: (a) activity value, (b) mobility value, and (c) complexity value.

The usage of all features produced higher accuracy compared to the individual activity or complexity but with the same accuracy with mobility. Mobility was considered as the best feature for having a lower number of features compared to all Hjorth descriptors. From mother wavelet selection, Bior1.5 produced the highest accuracy. Meanwhile, in the MLP configuration, N-15-5 produced the highest results.

Table 2. Accuracy for Hjorth descriptor on DWT using various mother wavelets and MLP configurations

MLP configuration	Features	Mother wavelet (%)				
		Haar	Db2	Db8	Bior1.5	Bior2.8
N-15-5	All	93.94	94.95	96.97	**97.98**	94.95
	Activity	87.88	93.94	90.91	89.90	89.90
	Mobility	96.97	93.94	95.96	**97.98**	93.94
	Complexity	88.89	92.93	92.93	96.97	90.91
N-30-5	All	94.95	94.95	96.97	96.97	95.96
	Activity	85.86	92.93	90.91	86.87	89.90
	Mobility	96.97	94.95	92.93	**97.98**	92.93
	Complexity	88.89	89.90	92.93	93.94	87.88
N-45-5	All	94.95	94.95	96.97	96.97	94.95
	Activity	91.92	91.92	90.91	87.88	90.91
	Mobility	96.97	93.94	92.93	96.97	94.95
	Complexity	89.90	91.92	92.93	94.95	87.88

The bolded number refers to the highest accuracy for each row.

The accuracy of each sub-band was tested using all of features, and all three features individually to see the effect of each sub-band on the accuracy as shown in Fig. 8. These results further confirmed that the utilization of the features in each sub-band overall generated a higher accuracy compared to the use of individual features. The highest accuracy was found at 97.98% for the sub-band D1. Theoretically, D1 sub-band occupying 2,000 to 4,000 Hz frequency had the insignificant information, but Hjorth descriptors calculated on the sub-band were able to distinguish each of lung sound class very well. This result was the same with mobility (8 features) but it needed fewer number of features for only requiring three features.

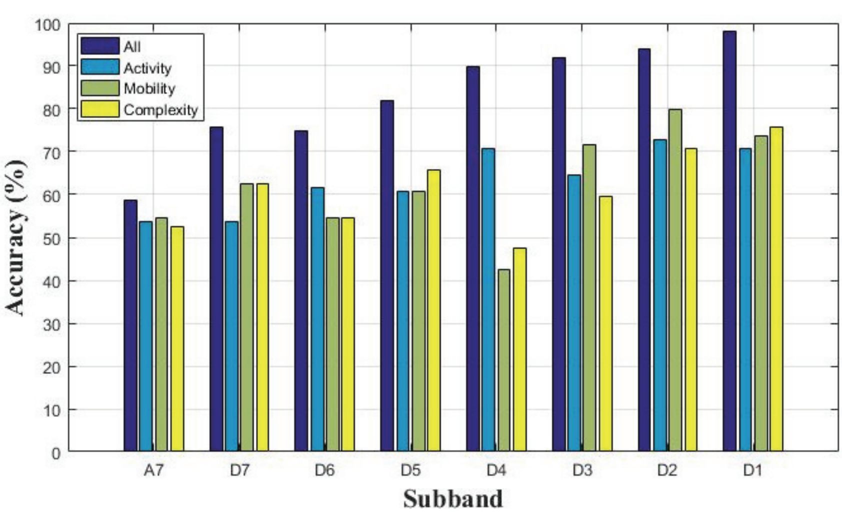


Fig. 8. Accuracy using each sub-band as an individual feature (Db2 and N-15-5).

Kandaswamy et al. [6] used DWT level 7 for lung sound classification with several different features. In the method proposed by Kandaswamy et al. [6], A1, D1, and D2 were not used because their amplitude was too small. Sub-band A7 occupied the frequency of 0–31.25 Hz; subband D2 had a frequency range of 1,000–2,000 Hz and D1 had the frequency in the range of 2,000–4,000 Hz. The third sub-band was considered to have no meaningful information as the fundamental frequency of lung sounds was in the range of 100 to 1,000 Hz [25]. In this study, we tested the use of features in sub-band D3-D7 with the results as shown in Fig. 9.

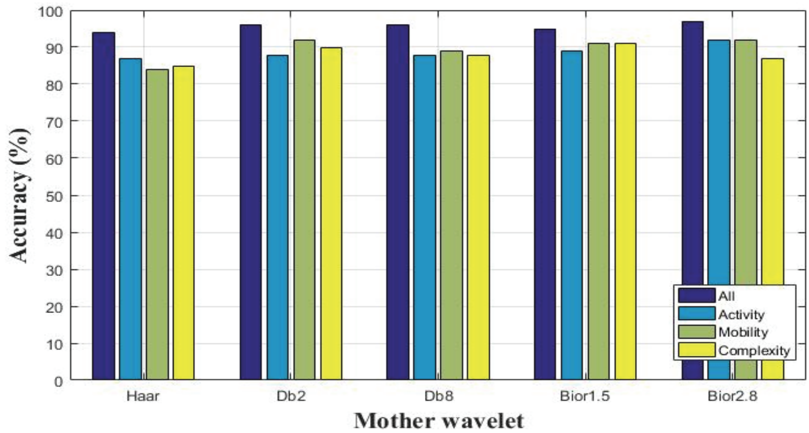


Fig. 9. Accuracy after sub-band A7, D1 and D2 elimination as used in [6].

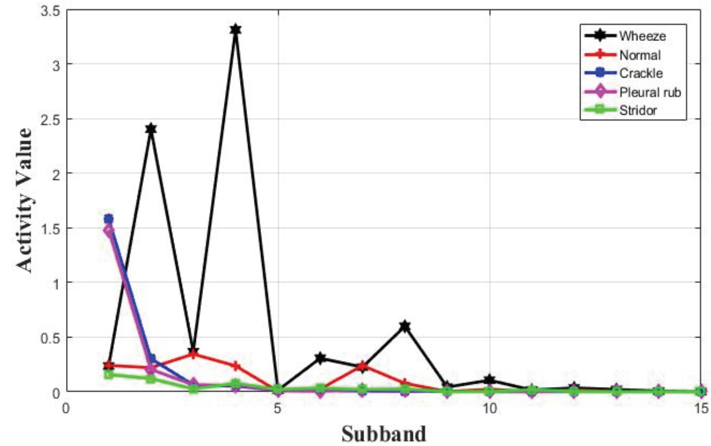
Fig. 9 shows that in the use of all features, the highest accuracy was found at 96.97%, lower than the accuracy using the entire sub-bands. The sub-band A7, D2, and D1 still had a contribution to accuracy even though considered to have an insignificant information content. Another thing shown in Fig. 6 is that the use of three Hjorth descriptor's parameters in this scheme could produce better accuracy compared to Hjorth descriptor's parameter individually. The reduction of the number of sub-bands decreased the number original feature from 24 to 15 features.

3.2 WPD Hjorth Descriptor

Fig. 10 displays the activity, mobility, and complexity values for each sub-band. For sub-band 9–15, the activity values tended to be lower in contrast to the values of mobility and complexity. All those features were used as the classification features in the next step.

Table 3 shows the accuracy obtained from Hjorth descriptors on WPD sub-band as features by using a similar testing scenario with the DWT. In general, the result shown in Table 3 was found better than that of Table 2 as more combinations generated the accuracy up to 98.99%. The activity individually reached the accuracy of 97.98%, while mobility and complexity produced the accuracy of 94.95% and 95.96% respectively.

Compared to the DWT method, WPD was more advantageous related to sub-band selection used for the calculation of the features. The WPD scenario, for 0–1,000 Hz frequency, was divided into eight subbands with a width of 125 Hz. On the other hand, for higher frequencies, a wider bandwidth was used since the information was considered less.



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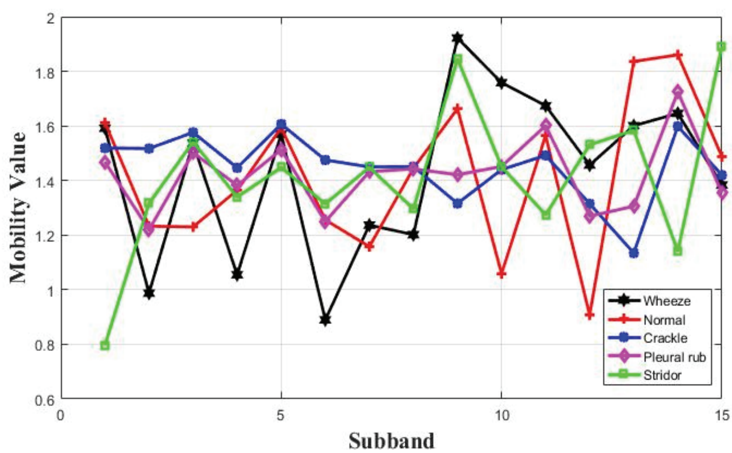

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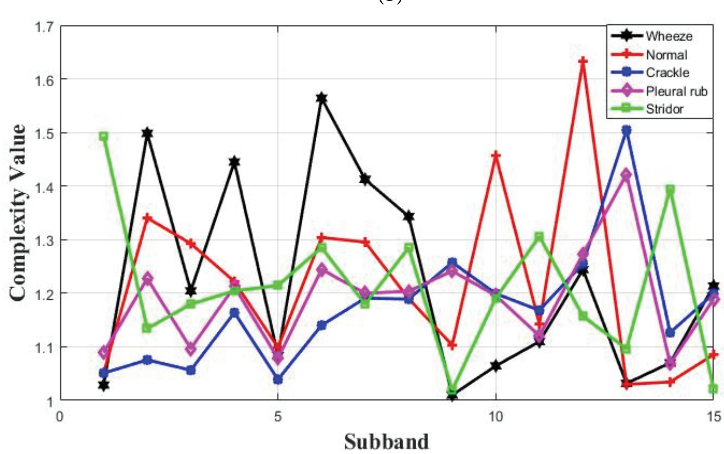

(c)

Fig. 10. Results for sub-band 1–15: (a) activity, (b) mobility, and (c) complexity.

The accuracy of each sub-band was tested to see the contribution of each subband (Fig. 11). Sub-band 15 at 2,000–4,000 Hz frequencies achieved the highest accuracy with the accuracy of 94.95% for all features. The second highest accuracy was found in sub-band 13 with the accuracy of 88.89%. It appeared that the use of the full features could produce much higher accuracy compared to individual feature. These results are consistent with previous findings in Fig. 8.

Table 3. Accuracy for Hjorth descriptor on WPD using various mother wavelets and MLP configurations

MLP configuration	Features	Mother wavelet (%)				
		Haar	Db2	Db8	Bior1.5	Bior2.8
N-15-5	All	**98.99**	97.98	93.94	**98.99**	96.97
	Activity	97.98	94.95	97.98	97.98	97.98
	Mobility	93.94	94.95	88.89	87.88	94.95
	Complexity	95.96	96.97	87.88	95.96	93.94
N-30-5	All	**98.99**	97.98	93.94	**98.99**	96.97
	Activity	97.98	96.97	97.98	95.96	95.96
	Mobility	91.92	94.95	88.89	89.90	94.95
	Complexity	95.96	93.94	88.89	95.96	93.94
N-45-5	All	**98.99**	97.98	93.94	**98.99**	96.97
	Activity	95.96	95.96	97.98	95.96	96.97
	Mobility	91.92	94.95	87.88	88.89	94.95
	Complexity	95.96	95.96	87.88	95.96	93.94

The information in the lung sounds mostly occupied the frequencies of <1,000 Hz. In the WPD scheme, sub-band 1–8 were at a frequency of 0–1,000 Hz. Fig. 12 shows the test result using sub-band 1–8 and the MLP N-15-5. In this scheme, the number of features could be reduced into 24 of 45 features. The accuracy of 98.99% was achieved by activity using wavelet Bior1.5. This result was even better than the one using 24 features as shown in Fig. 9.

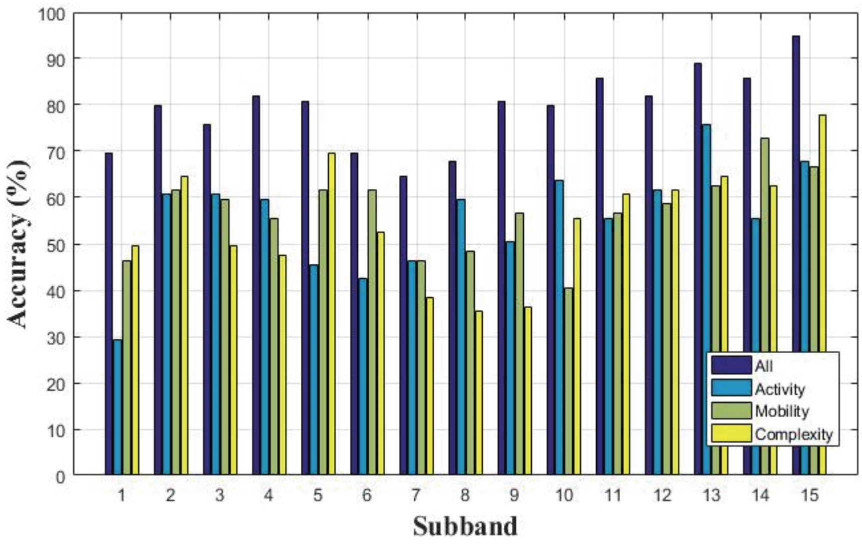

Fig. 11. Accuracy of each sub-band.

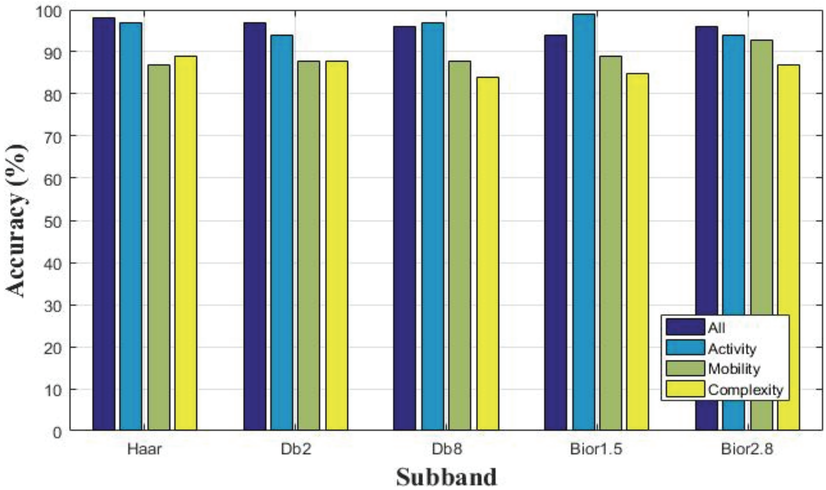

Fig. 12. Accuracy using eight first sub-band (0–1,000 Hz).

Table 4. Comparison with other methods

No	Dataset	Features	Number of features	Classifier	Accuracy (%)	Ref.
1	120 data, 6 classes	Mean absolute values, average power, standard deviation, Ratio of the absolute mean values of adjacent sub-band on DWT	19	BP-NN	92	[6]
2	140 data, 2 classes	Similar with No. 1 plus skewness and kurtosis	46	MLP	90	[7]
3	48 data, 6 classes	Similar with No. 1	19	PNN, SVM	96.67 (average)	[8]
4	81 data, 5 classes	Hjorth descriptor	3	MLP	83.95	[11]
5	81 data, 5 classes	Hjorth descriptor on multi-scale	15	MLP	95.06	[12]
6	81 data, 5 classes	EMD Hjorth descriptor	10	MLP	97.98	[13]
7	81 data, 5 classes	MSLD Hjorth descriptor	10	MLP	97.98	[14]
8	99 data, 5 classes	Hjorth descriptor on DWT	24	MLP	97.98	Proposed method
9	99 data, 5 classes	Hjorth descriptor on WPD	8	MLP	98.99	Proposed method

3.3 Comparison with Other Methods

There are three studies on lung sounds classification using DWT order 7, as mentioned in this study [6–8]. The differences between this research and the previous research are related to the data used, sampling frequency, feature extraction, and classifier. In addition, the use of Hjorth descriptor was tested on the overall signal and multi-scale analysis for lung sounds classification with the same data [11]. A comparison between the proposed method and method in previous studies is depicted in Table 4.

Table 4 shows that the Hjorth descriptor on WPD after sub-band reduction produced the best accuracy of 98.99% and generated the fewest number of features (eight features). Hjorth descriptor on DWT also produced the accuracy of 98.99%. However, DWT required more features to achieve the same accuracy. Hjorth descriptor measurement on wavelet sub-band produced a better accuracy than Hjorth descriptor in multi-scale signal [11]. The advantages of the proposed method are in the ease of selecting the sub-band to be used as a feature. As shown in Figs. 4 and 6, we can choose the sub-band where the Hjorth descriptor will be calculated. We, if necessary, can vary the sub-band to be used by changing the decomposition level. In this case, WPD is more flexible than DWT.

4. Conclusions

In this paper, we proposed Hjorth descriptors measurement in wavelet sub-band by using DWT and WPD for features extraction on lung sound classification. At DWT level 7, the proposed method simultaneously produced 24 features that could be reduced into 15 features and still maintained high accuracy. On the other hand, for the WPD level 5, we used eight first sub-bands to produce the highest accuracy of 98.99% with eight features. Hjorth descriptor measurement on wavelet sub-band was better than Hjorth descriptor in the multi-scale scheme for lung sound classification. In this research, we used all wavelet sub-bands as used in the previous study. Future work will focus on the optimum sub-band selection using some criteria to achieve the highest accuracy. In addition, Hjorth descriptor can be replaced by other signal complexity metrics to produce lung sound features.

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