Lung sound classification using multiresolution Higuchi fractal dimension measurement

Achmad Rizal[1], Risanuri Hidayat[2], Hanung Adi Nugroho[2], Willy Anugrah Cahyadi[1]
[1]School of Electrical Engineering, Telkom University, Bandung, Indonesia
[2]Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia

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ABSTRACT

Lung sound is one indicator of abnormalities in the lungs and respiratory tract. Research for automatic lung sound classification has become one of the interests for researchers because lung disease is one of the diseases with the most sufferers in the world. The use of lung sounds as a source of information because of the ease in data acquisition and auscultation is a standard method in examining pulmonary function. This study simulated the potential use of Higuchi fractal dimension (HFD) as a feature extraction method for lung sound classification. HFD calculations were run on a series of *k* values to generate some HFD values as features. According to the simulation results, the proposed method could produce an accuracy of up to 97.98% for five classes of lung sound data. The results also suggested that the shift in HFD values over the selection of a time interval *k* can be used for lung sound classification

Corresponding Author:

Achmad Rizal
School of Electrical Engineering, Telkom University
Telekomunikasi st., no. 1, Bandung-40287, Indonesia
Email: achmadrizal@telkomuniversity.ac.id

1. INTRODUCTION

Lung sounds are important pieces of information used by physicians in detecting abnormalities either in the lungs or respiratory tract [1]. Though various medical imaging techniques have been developed, lung auscultation sounds remain an effective media for diagnosing lung diseases. Various digital signal processing techniques have been developed to reduce subjectivity in analyzing lung sounds [2], as well as classification methods applied to obtain high accuracy in the classification of lung sounds [3].

Fractal dimension analysis is a highly reliable method for biomedical signal analysis [4]. Higuchi's fractal dimension (HFD) is one of the fractal dimension measurement methods that is known to be a quite efficient and accurate way to measure the fractal dimension of a signal [5], [6]. HFD is widely used in the analysis of the biological signal such as electromyogram (EMG), and electrocardiogram (ECG). The classification of several classes of limb motion by EMG signals has been carried on [7], and some other fractal methods were combined with relevant vector machine (RVM) were used to distinguish seven classes of EMG data. HFD and Katz were measured on wavelet sub-band for detecting voice pathology [8]. HFD was also utilized to identify heart rate variability (HRV) on a cardiac patient ECG stress test [9]. HFD measurement depends on the value of the specified maximum time interval k_{max}. In previous studies, HFD was commonly measured at only one particular value of k_{max} [7]–[9]. Some researchers tried to analyze the HFD value in a range of k_{max} to obtain an optimum HFD value [10].

Kitaoka *et al.* [11] stated that the human airway tree system has fractal properties. The fractality of the human airway tree indicates that the lung sounds produced will also be fractal. Gnitecki and Moussavi [12] have tested the fractality of lung sounds using three fractal methods, Katz fractal dimension (KFD), variance fractal dimension (VFD), and Katz-Sevcik fractal dimension (KSFD). The results prove that the fractality of lung sounds can be used to differentiate between normal and abnormal lung sounds. In another study, Rizal *et al.* [13] used fractal dimensions at several scales for lung sound classification. In lung sounds, a multiscale process called coarse-grained procedure [13] is carried out, and then the fractal dimension is calculated as a feature. Tests were carried out on eight fractal dimensions, and the Petrosian C fractal dimension produced the highest accuracy. Suppose in the study, the fractal dimension is calculated on the multiscale processed signal; HFD can be calculated at various resolutions to make several fractal dimension values as in [8].

In this study, HFD measurement with a resolution range of k_{max} values for signal analysis was investigated. The inappropriateness of the obtained HFD value was used as the features of the signal. This method was proved to be an effective way as seizure EEG signal classification method [14]. For an example case, we used some synthetic and real measured lung sound signals. To evaluate the accuracy of the resulting features, multilayer perceptron (MLP) was used as the classifier for lung sound classification. In this paper, we used HFD value shifting produced from a range of k_{max} values as features for lung sound classification. Several HFD values from this process will hopefully generate higher accuracy compared with a single value HFD.

This paper is organized as: section 2 describes the proposed method and material employed in this study. Section 3 describes the simulation results and discussion of the research. Section 4 concludes the results of this study and describes the potential future work.

2. METHOD

Figure 1 shows the proposed system. The input signal was normalized and the subsequent process was the measurement of HFD for one hundred k_{max} values, i.e., k_{max}=1, 2, 3, …, 100. The HFD values obtained were then used as the features of the input signal. Feature selection was performed afterwards to find the range of k_{max} values on HFD that produce the highest accuracy for lung sound classification. Meanwhile, for the classification process, MLP was used as a classifier. The classification result was compared to lung sound data label to count the classification accuracy. A detailed description is presented in the following subsections.

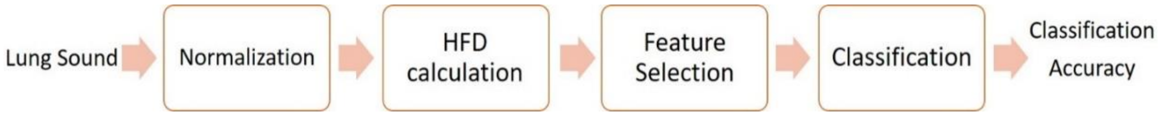


Figure 1. Proposed method

2.1. Higuchi fractal dimension

The Higuchi method (HFD) is the one-dimensional fractal measurement algorithm generally applied in a biomedical signal [5]. The advantages of the HFD are the high accuracy and efficient way to measure the fractal dimension (FD) [15]. If a signal X_m^k has a sample size *N*, it can set up a subset signal with *k* time interval with different resolutions as shown in (1).

$$X_m^k: x(m), x(m+k), x(m+2k), \dots, x\left(m + \left[\frac{N-m}{k}\right]k\right) \quad (1)$$

The value of *m* in (1) indicates the start time (*m*=1, 2, ..., k). Using (1), we will have a set of new signals with different resolution. Furthermore, the length of the curve of X_m^k, i.e., $l_m(k)$ is defined as in (2).

$$l_m(k) = \frac{\sum_{i=k}^{\lfloor N-m/k \rfloor} |x(m+ik)-x(m+(i-1)k)|(N-1)}{(\lfloor N-m/k \rfloor)k} \quad (2)$$

The $(\lfloor N-m/k \rfloor)k$ denominator is a normalization factor. Based on (2), we can calculate the length of the curve for each interval *k* as described in (3).

$$\mathrm{L(k)} = \sum_{\mathrm{m=1}}^{\mathrm{k}} \mathrm{l_m(k)} \tag{3}$$

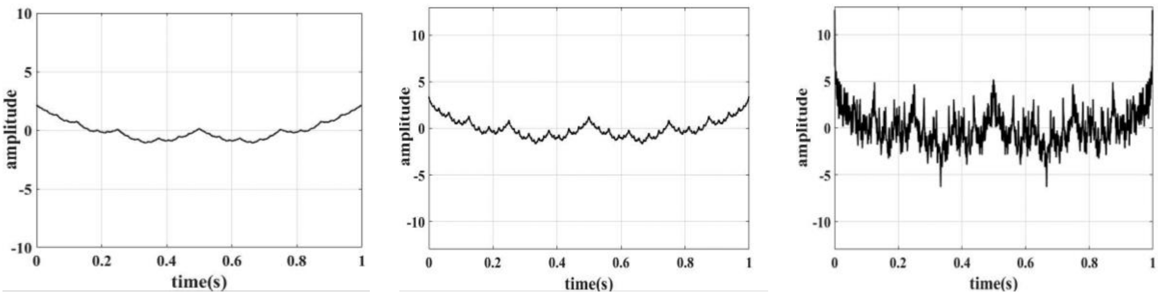
From the slope of the plot $ln\big(L(k)\big)$ against $ln(1/k)$, we can obtain FD. Where $L(k)$ is the length of curve for each interval k. Fractal dimension were derived from the relationship $L(k) \propto k^{-D}$, the HFD was denoted as D.

2.2. Synthetic input signal

Synthetics signal were generated to assess the HFD measurement performance. The signal had some specific characteristics, thus HFD performance can be observed in fractal dimension measurement on the signals. We used Weierstrass cosine function (WCF) [16], as expressed in (4).

$$W_H(t) = \sum_{k=0}^{\infty} \gamma^{-kH} \cos(2\pi\gamma^k t),\ 0 < H < 1,\ \gamma > 1 \tag{4}$$

WCF is a continuous function but is differentiable nowhere. The fractal dimension of WCF function is D=2–H, as H is Haussdorf dimension [17]. With γ is an integer value, the function will be periodic with *period*=1. In this study, we used N=1,000, γ=2, H=0.1–0.9 to obtain a signal with the fractal dimensions of 1.9, 1.7, 1.5, 1.3, and 1.1, respectively. In addition, Figure 2 shows the WCF signal with different FD value. Figure 2(a) shows WCF with FD=1.1, Figure 2(b) shows WCF with FD=1.5, while WCF with FD=1.9 is presented in Figure 2(c). WCF with higher FD value has higher fluctuation.



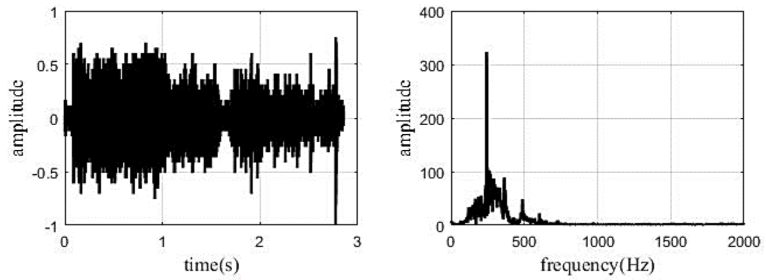
(a) (b) (c)

Figure 2. WCF signal with fractal dimension (a) FD=1.1, (b) FD=1.5, and (c) FD=1.9

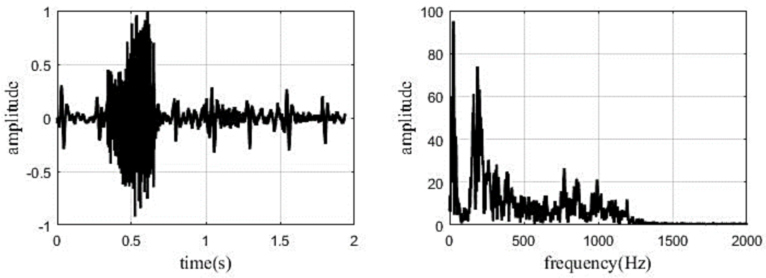
2.3. Lung sound dataset

The lung sound data were gathered from several online sources and had been used in our previous study [18], [19]. Data were obtained from the internet as in [20] and CD complimentary books [21]. The data consisted of five classes with 22 normal bronchial, 18 wheezes, 20 crackles, 19 pleural rubs, and 20 stridors. The data were recorded from 9 patients with a range of age from two weeks old to 79 years old. The wheeze data were taken from the patient with chronic obstructive lung disease and asthma, while crackle sounds were recorded from the patient with interstitial pulmonary fibrosis and cystic fibrosis [18]. Stridors were recorded from patient with laryngeal web and patient with viral croup and asthma. Each lung sound has a length of one cycle of respiration (one inspiration and one expiration) with the sample number 15,000-34,000 as the sampling frequency of 8,000 Hz and wave format. Lung sound data is taken from recordings on the internet so that the lung sound data is clean from heart sounds which are the source of noise from lung sounds. The process of removing heart sounds from the lungs is a separate research topic [22].

Normal bronchial sound is a common lung sound heard in the [23]. The wheeze sound is a lung sound with high pitch, continuous, musical characteristics, and has a dominant frequency in the range of 400-600 Hz [24]. Asthma is one of lung diseases that produces wheeze sound. Asthma is caused by an obstruction of the airways [25]. Meanwhile, the crackle is a nonmusical, discontinuous, and short duration lung sound. The lung diseases that produce this sound are chronic bronchitis, asbestosis, and pneumonia [1]. Pleural rub or friction rub occurs as pleural friction in pleurisy diseases [1]. A high-pitch wheeze commonly called a stridor, occurs due to the obstruction of the central airways [2]. The five classes of data have different properties expected to be classified correctly by the proposed method. Examples of raw data for both wheezing and stridor sound are shown in Figure 3. Figure 3(a) shows wheeze sound and its frequency spectrum, while Figure 3(b) displays stridor sound and its frequency spectrum. Stridor has higher frequency component compare to wheeze as its definition explained before.



(a)



(b)

Figure 3. Plot of lung sound signal and its frequency spectrum (a) wheeze and (b) stridor

3. RESULTS AND DISCUSSION

3.1. HFD measurement result on synthetic signal

HFD measurement with k_{max}=1, 2, 3, …, 100 for WCF signal with FD=1.1–1.9 is shown in Figure 4. For k_{max}=1, HFD=0 occurred due to $X_m^k = X_1^1$ indicating a signal $x(n)$ in itself. The zero HFD value could be ignored as being inaccurate. Meanwhile, in line with the increase in the value of k_{max}, there was a tendency for the HFD of WCF signal to increase [16]. The HFD value became higher than the actual FD of WCF. The calculation of statistical values of HFD at WCF is shown in Table 1.

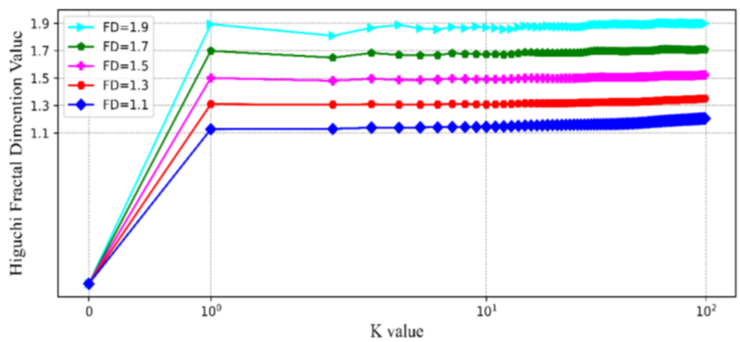


Figure 4. HFD measurement for WCF for k_{max}=1, 2, 3, …, 100

Table 1. HFD (min, max, mean, SD) for each signal

Input Signal	HFD			
	Min	Max	Mean	SD
WCF FD=1.1	1.1268	1.2062	1.1601	0.0257
WCF FD=1.2	1.2129	1.2751	1.2367	0.0203
WCF FD=1.3	1.3058	1.3517	1.3211	0.0156
WCF FD=1.4	1.3944	1.4348	1.4100	0.0131
WCF FD=1.5	1.4804	1.5230	1.5017	0.0127
WCF FD=1.6	1.5634	1.6140	1.5935	0.0148
WCF FD=1.7	1.6480	1.7084	1.6866	0.0173
WCF FD=1.8	1.7238	1.8065	1.7811	0.0217
WCF FD=1.9	1.8106	1.8999	1.8786	0.0222

From Table 1, it can be observed that the HFD value of WCF is quite close to the theoretical value for higher values of k_{max}. The standard deviation (SD) of HFD is quite small. It can be noted that the HFD is very accurate for the fractal dimension measurement of a signal.

3.2. HFD measurement result on lung sound

Figure 5 shows some sample measurement results of HFD on five types of lung sounds. Wheeze, crackle, and friction rub tended to have a similar pattern. The HFD was relatively high at k_{max}=2, but then declined, and rose again. Meanwhile, the bronchial and stridor had a pattern that tended to increase from k_{max}=2. The difference of this pattern would be tested to see it is capable of being used as a differentiator between the data class of lung sounds. Minimum, maximum, average, and standard deviation of HFD values is summarized in Table 2.

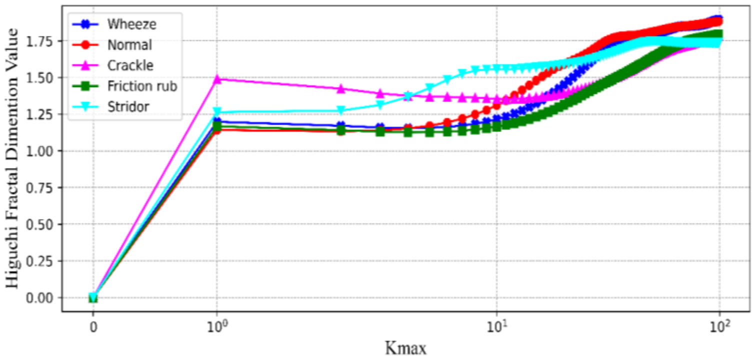


Figure 5. HFD measurement for k_{max}=1, 2, 3, …, 100 for typical lung sound

Table 2. HFD for each lung sound data class

Data class	HFD			
	Min	Max	Mean	SD
Wheeze	1.073576	1.916041	1.683621	0.228785
Normal	1.018532	1.91493	1.644381	0.294868
Crackle	1.022018	1.880041	1.590555	0.197504
Friction rub	1.048141	1.851147	1.559593	0.240628
Stridor	1.230591	1.772475	1.674746	0.108781

Table 2 shows that stridor has the lowest standard deviation for HFD value among the lung sounds. Although stridor has large fluctuation in time domain since it has high frequency component above 1,000 Hz, the stridor only appears in inspiration phase. Stridor had lower HFD values compare to wheeze or other lung sound. The HFD value in normal signals tends to be in the middle of pathology lung sounds caused by pathology sounds having certain characteristics related to their frequency components. For example, wheeze has a high-frequency component, so the signal fluctuations in the frequency domain are relatively high. This makes the HFD wheeze value relatively high. Meanwhile, crackle has a lower average HFD value than normal lung sounds because crackle sounds have a rather discontinuous sound. The frequency spectrum tends to be at low frequencies. Low frequency can be seen as low fluctuations in the time domain. This low fluctuation causes a low HFD value. Figure 6 shows the lung sound from all classes with both spectrum and HFD values for k_{max}=2-100. Figure 6(a) shows a plot of the wheeze sound and its frequency spectrum along with the resulting characteristics of the HFD with k_{max}=2-100. Meanwhile, Figure 6(b) shows the signal plot, frequency spectrum, and features resulting from the HFD with k_{max}=2-100 for normal lung sound. Crackle's signal plot, frequency spectrum, and HFD value is displayed in Figure 6(c). Pleural rub plot is presented in Figure 6(d), while Figure 6(e) display stridor, plot in time domain, frequency domain, and HFD value. As mention before, although the stridor has a frequency component >1,000 Hz and high fluctuations in the time domain, it has an HFD with a low standard deviation. This is because stridor appears only during the inspiratory phase.

Wheeze and crackle have different characteristics, i.e., continuous and discontinuous, respectively. Larger time interval, k_{max}, means more samples of the signal that will be bypassed. It is going to make the discontinuity of the crackle not visible. In addition, the slope of the plot $ln(L(k))$ against $ln(1/k)$ will be smoother and result in greater HFD value [8]. The larger HFD values for larger k_{max} values have become a common pattern for all lung sound classes. The HFD difference in a range of k_{max} is in the HFD value curve as in Figures 5 and 6. This curvature is influenced by the distribution of the lung sound sample signal. High fluctuating pulmonary sound with relatively equal amplitude as wheeze will produce a relatively large HFD while high-fluctuated signals with uneven amplitude such as stridor will produce relatively small HFDs.

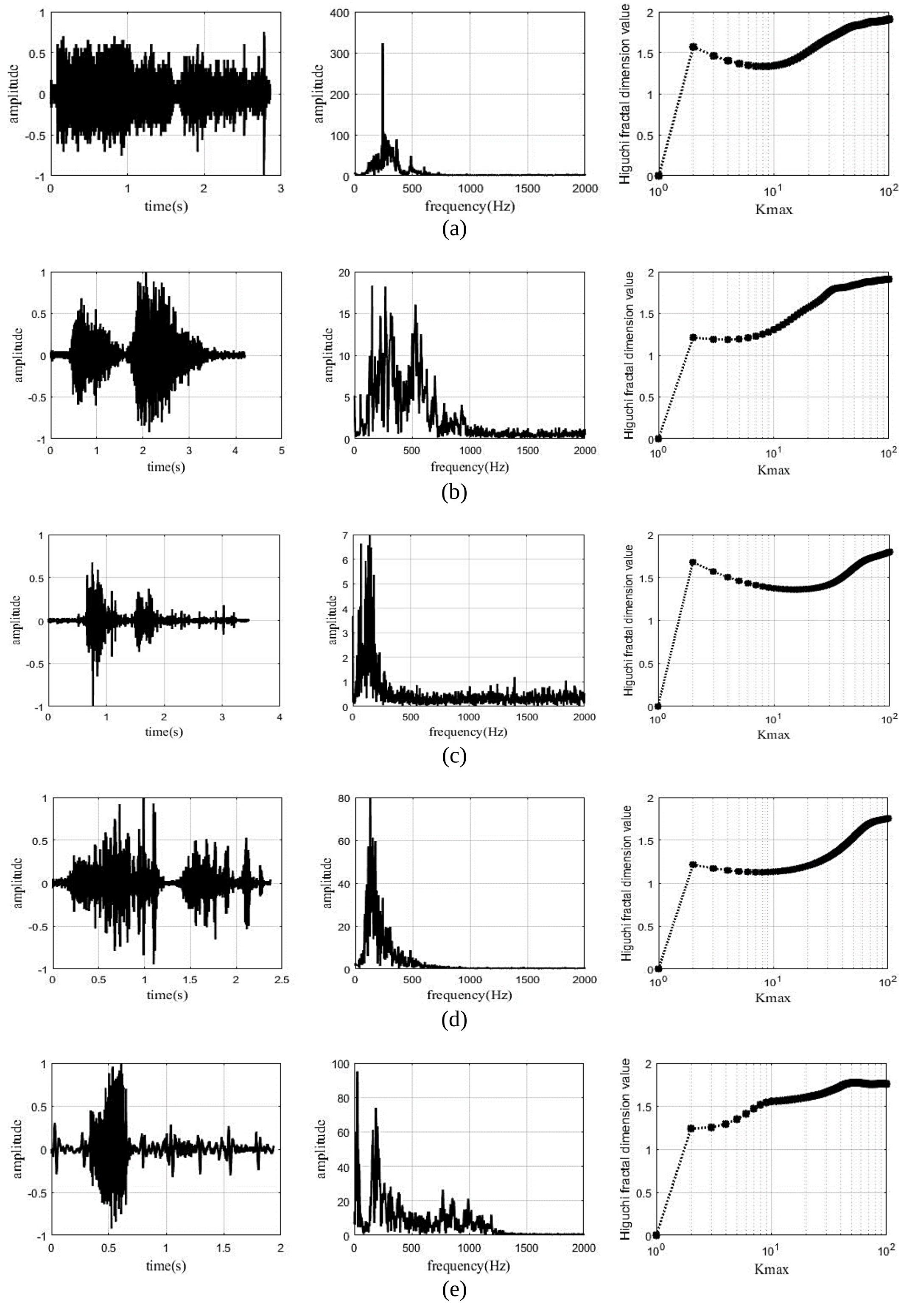


Figure 6. Signal, frequency spectrum, and HFD value for k_{max}=2-100 (a) wheeze, (b) normal lung sound, (c) crackle, (d) pleural rub, and (e) stridor

From Table 2, the HFD values were in the range of 1.0–1.9 with an average value of around 1.5–1.6. Using the analysis of variance (ANOVA) statistical test, we found the F-value for HFD value using k_{max}=2–100 is 2647.455. A higher F-value indicates a better performance for separating data than a lower F-value. The F-value is inversely related to P-value. Table 3 shows the F-value and P-value of ANOVA analysis for several combinations of k_{max} for HFD measurement. Table 3 indicates that HFD values using k_{max}=2–100 produce very high F-value and very low P-value. F-value tended to decrease when we reduce the number of HFD values.

Table 3. F-value and P-value for each range of k_{max} using ANOVA

k_{max}	F-Value	P-Value
2–100	2647.455	0
2–50	1473.032	0
2–40	1188.647	0
2–30	1043.025	0
2–20	1117.155	0
2–10	569.234	1.4E-227
2–5	171.027	4.48E-80

3.3. HFD measurement for lung sound classification

In this study, MLP was applied with the altered number of hidden neurons, i.e., 15, 30, and 45 [26]. Meanwhile, for validation, we used N-fold cross validation (NFCV) [27]. In this case, a three-fold CV was applied, so each of the data sets would consist of 6–8 data. By choosing N=3 for N-fold CV, we divide the data into three sets, 2 data sets are training data, and 1 data set is test data. The testing process is carried out three times until all data sets have become test data. Accuracy is the average of the three accuracies for each iteration. The advantage of this method is that it can avoid overfitting.

To see the range of values k_{max} producing the highest accuracy, we evaluated it using HFD generated by the k_{max} value in a particular range. The accuracy obtained is as shown in Table 4. The highest accuracy achieved was 93.94% with a range of k_{max} from 2 to 50, then 2 to 40, and finally 2 to 30. The range of k_{max}=2–30 was considered the best due to fewer number of features used. Meanwhile, the k_{max} value with a narrower range produced the lower accuracy. As in Figure 5, the difference pattern is quite prominent in the range of k_{max}=2–30.

Table 4 display the accuracy of lung sound classification using different number of features and different MLP configuration. In Table 4, the feature selection is carried out by reducing the amount k_{max} used to measure the HFD. Reducing the number of features and using the right MLP parameters are proven to produce higher accuracy than 100 HFD values.

The use of different k_{max} values in the HFD calculation produced different HFD value. This occurred because the signal X_m^k in (1) could produce different series. Next, the calculation of the (2) and (3) would also be different. Even if the value of HFD produced only slight shifts, the changes in the value of HFD at a certain interval k_{max} value were quite capable of distinguishing between data classes. The improved accuracy achieved was high considering the same data by only using one value of HFD (k_{max}=40), producing a maximum of 66.67% accuracy. The standard criterion to choose k_{max} was not provided [28].

However, some researchers tried to make some approach to choose appropriate k_{max} value. The author stated in [29] that in order to select an appropriate k_{max} value, HFD values were plotted against a range of k_{max}. The point where the FD plateaus was considered a saturation point, and that k_{max} value was chosen. In [29], k_{max}=60 was used as in [30].We choose k_{max}=40 for comparison because k_{max}=40 produce the nearest WCF's HFD value with theoretical FD for FD≥1.5. Study in [4] showed that Higuchi's algorithm provided most accurate FD for synthetic signal with FD≥1.5.

The disadvantages of the proposed method were related to the number of features more than using a single value of k_{max}. However, with the four features, such as the results obtained, the resulted accuracy was very high away from more than the use of a single value HFD. The use of HFD for lung sound analysis is rarely used before. The fractal dimension often used for lung sound analysis could be KFD, VFD, and SFD [12]. Fractal dimension is used for the heart sound reduction at lung sound recordings [31]. Meanwhile, KFD and SVD combined with wavelet are used to improve the sound quality of lung and bowel sounds for the detection of Crackle and other abnormalities [32], [33]. HFD was rarely used for lung sounds analysis for calculations involving a linear regression process on a double logarithmic plot of $L(k)$ and k to determine the value of HFD. KFD, SFD, and SVD can be directly calculated from a series of signals.

Table 5 presents accuracy of lung sound classification using MLP and seven fractal dimensions. The fractal dimensions are KFD, VFD, and SVD as used in [12] and box-counting fractal dimension (BCFD), HFD (k_{max}=40), Petrosian C and Petrosian D as used in [4]. The result shows that the accuracy is about

62.63%-72.73%. Single fractal dimension cannot produce sufficient accuracy for lung sound classification. Some improvement must be done on those FD measurements if we want to increase the accuracy, for example, combine with other methods such as wavelet as in [33].

The same approach was used to detect Alzheimer's disease (AD) through the EEG signal [34]. The results showed that in patients with AD, HFD values were calculated in the range of k_{max}=2–128, tending to be lower than normal and ordinary aging. HFD proved to be sensitive to changes in the nervous system due to aging and AD [31]. Although the proposed method almost the same with study in [26], there some differences in this paper. In the study of [34], 127 HFD values were needed as features for EEG signal. Meanwhile, in our study, the result showed that HFD values with k_{max}=2–30 produced higher accuracy than HFD values with k_{max}=2–100.

In the next stage, we test which features play the most role using feature subset selection (FSS) [35]. The FSS method chosen was wrapper subset selection (WSS), which obtained 4 HFD characteristics (k_{max}=5, 7, 11, and 99), resulting in the highest accuracy of 97.98%, better than the accuracy shown in Table 4. This proves that the proposed method is capable of producing high enough accuracy with the right selection of features. Another study combined the time series method with the fractal method to analyze several breath sounds [36], [37]. The use of several different features will directly add to the computational complexity. Meanwhile, in this study, HFD was calculated repeatedly with different resolutions.

In this study, we did not discuss the effect of the data length on HFD value as done in [38]. The data used in this study had 15,000–34,000 samples. The focus of this study was not measuring the accuracy of the HFD method for fractal dimension measurement. HFD values shifting due to changes in the value of k_{max} were used as features of lung sound signal. The results showed that the selection of an appropriate range of k_{max} value could produce a very high accuracy.

In this study, the data set used was limited, making it impossible to separate training data, testing data, and other data for verification. But in this study, we used N-fold CV, so the performance test was carried out three times to prove that the performance of the proposed method was good enough. In another study, a larger data set was used with fairly high accuracy in the case of EEG signals. Using larger data sets with better testing will challenge future research. This proposed method is expected to be an option for other biomedical signal processing methods.

Table 4. Accuracy of lung sounds classification using MLP

k_{max} value	Accuracy (%) Number of hidden neurons		
	15	30	45
2–100	90.91	91.92	91.92
2–50	93.94	92.93	93.94
2–40	92.93	93.94	93.94
2–30	91.92	93.94	93.94
2–20	91.92	89.9	91.92
2–10	89.9	86.87	87.88
2–5	78.79	73.74	77.78

Table 5. Accuracy of lung sound classification using MLP and fractal dimension

Fractal dimension	Accuracy (%)
VFD	72.73
SFD	70.71
BCFD	68.69
KFD	66.67
HFD	66.67
Petrosian C	62.63
Petrosian D	62.63

4. CONCLUSION

This study describes the measurement of HFD with various resolutions for feature extraction in the classification of lung sounds. The selection of different k_{max} values on HFD measurement produces some different fractal dimension values. The HFD values with this particular a range of k_{max} can be utilized as the features for the classification of lung sounds. The results showed the highest accuracy of 97.98% achieved for HFD with k_{max} equals to 5, 7, 11, and 99. Further research is required to see the effect of the data length and shifting of the data on the accuracy. In addition, exploration of the use of this method for other biomedical signals is interesting to do or exploration using more advanced classification methods.

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REFERENCES

[1] A. Bohadana, G. Izbicki, and S. S. Kraman, "Fundamentals of lung auscultation," *New England Journal of Medicine*, vol. 370, no. 8, pp. 744–751, Feb. 2014, doi: 10.1056/NEJMra1302901.
[2] A. Rizal, R. Hidayat, and H. A. Nugroho, "Signal domain in respiratory sound analysis: methods, application and future development," *Journal of Computer Science*, vol. 11, no. 10, pp. 1005–1016, Oct. 2015, doi: 10.3844/jcssp.2015.1005.1016.
[3] R. Palaniappan, K. Sundaraj, and N. U. Ahamed, "Machine learning in lung sound analysis: a systematic review," *Biocybernetics and Biomedical Engineering*, vol. 33, no. 3, pp. 129–135, Jan. 2013, doi: 10.1016/j.bbe.2013.07.001.
[4] R. Esteller, G. Vachtsevanos, J. Echauz, and B. Litt, "A comparison of waveform fractal dimension algorithms," *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, vol. 48, no. 2, pp. 177–183, 2001, doi: 10.1109/81.904882.
[5] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," *Physica D: Nonlinear Phenomena*, vol. 31, no. 2, pp. 277–283, Jun. 1988, doi: 10.1016/0167-2789(88)90081-4.
[6] K. Najarian and R. Splinter, *Biomedical signal and image processing*. Taylor and Francis, 2012.
[7] C. A. M. Lima, A. L. V Coelho, R. C. B. Madeo, and S. M. Peres, "Classification of electromyography signals using relevance vector machines and fractal dimension," *Neural Computing and Applications*, vol. 27, no. 3, pp. 791–804, Apr. 2016, doi: 10.1007/s00521-015-1953-5.
[8] Z. Ali, I. Elamvazuthi, M. Alsulaiman, and G. Muhammad, "Detection of voice pathology using fractal dimension in a multiresolution analysis of normal and disordered speech signals," *Journal of Medical Systems*, vol. 40, no. 1, Jan. 2016, doi: 10.1007/s10916-015-0392-2.
[9] G. D'addio *et al.*, "Fractal behavior of heart rate variability during ECG stress test in cardiac patients," in *2014 8th Conference of the European Study Group on Cardiovascular Oscillations (ESGCO)*, May 2014, pp. 155–156, doi: 10.1109/ESGCO.2014.6847566.
[10] S. Spasic, A. Kalauzi, G. Grbic, L. Martac, and M. Culic, "Fractal analysis of rat brain activity after injury," *Medical and Biological Engineering and Computing*, vol. 43, no. 3, pp. 345–348, Jun. 2005, doi: 10.1007/BF02345811.
[11] H. Kitaoka, R. Takaki, and B. Suki, "A three-dimensional model of the human airway tree," *Journal of Applied Physiology*, vol. 87, no. 6, pp. 2207–2217, Dec. 1999, doi: 10.1152/jappl.1999.87.6.2207.
[12] J. Gnitecki and Z. Moussavi, "The fractality of lung sounds: A comparison of three waveform fractal dimension algorithms," *Chaos, Solitons and Fractals*, vol. 26, no. 4, pp. 1065–1072, Nov. 2005, doi: 10.1016/j.chaos.2005.02.018.
[13] A. Rizal, H. A. Nugroho, and R. Hidayat, "Fractal dimension for lung sound classification in multiscale scheme," *Journal of Computer Science*, vol. 14, no. 8, pp. 1081–1096, Aug. 2018, doi: 10.3844/jcssp.2018.1081.1096.
[14] A. Rizal and R. Estananto, "Epileptic EEG signal classification using multiresolution Higuchi fractal dimension," *International Journal of Engineering Research and Technology*, vol. 12, no. 4, pp. 508–511, 2019.
[15] I. Wijayanto, R. Hartanto, and H. A. Nugroho, "Higuchi and Katz fractal dimension for detecting interictal and ictal state in electroencephalogram signal," in *2019 11th International Conference on Information Technology and Electrical Engineering (ICITEE)*, Oct. 2019, pp. 1–6, doi: 10.1109/ICITEED.2019.8929940.
[16] G. H. Hardy, "Weierstrass's non-differentiable function," *Transactions of the American Mathematical Society*, vol. 17, no. 3, pp. 301–325, 1916, doi: 10.1090/S0002-9947-1916-1501044-1.
[17] B. Hunt, "The Harsdorf dimension of graphs of Weierstrass functions," *Proceedings of the American Mathematical Society*, vol. 126, no. 3, 1998, pp. 791–800, doi: 10.1090/S0002-9939-98-04387-1.
[18] "The R.A.L.E repository," R.A.L.E. Lung Sounds, http://www.rale.ca/Repository.htm (accessed Jul. 22, 2015).
[19] A. Rizal and A. Puspitasari, "Lung sound classification using wavelet transform and entropy to detect lung abnormality," *Serbian Journal of Electrical Engineering*, vol. 19, no. 1, pp. 79–98, 2022, doi: 10.2298/SJEE2201079R.
[20] Chris, "The auscultation assistant," https://www.wilkes.med.ucla.edu/lungintro.html (accessed May 01, 2015).
[21] R. L. Wilkins, J. E. Hodgkin, and B. Lopez, *Lung sounds: a practical guide with audio CD*. Mosby, 1996.
[22] A. M. Mekala and S. Chandrasekaran, "Heart sound interference cancellation from lung sound using dynamic neighbourhood learning-particle swarm optimiser based optimal recursive least square algorithm," *International Journal of Biomedical Engineering and Technology*, vol. 34, no. 2, 2020, doi: 10.1504/IJBET.2020.111000.
[23] H. Pasterkamp, S. S. Kraman, and G. R. Wodicka, "Respiratory sounds," *American Journal of Respiratory and Critical Care Medicine*, vol. 156, no. 3, pp. 974–987, Sep. 1997, doi: 10.1164/ajrccm.156.3.9701115.
[24] A. Rizal, R. Hidayat, and H. A. Nugroho, "Lung sound classification using Hjorth descriptor measurement on wavelet sub-bands," *Journal of Information Processing Systems*, vol. 15, no. 5, pp. 1068–1081, 2019.
[25] F. Z. Göğüş, B. Karlık, and G. Harman, "Identification of pulmonary disorders by using different spectral analysis methods," *International Journal of Computational Intelligence Systems*, vol. 9, no. 4, 2016, doi: 10.1080/18756891.2016.1204110.
[26] M. Abbasinia, F. Farokhi, and S. Javadi, "Predicting acute hypotensive episode by using hybrid features and a neuro-fuzzy network," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 24, pp. 3335–3344, 2016, doi: 10.3906/elk-1403-117.
[27] R. Kohavi and G. H. John, "Wrappers for feature subset selection," *Artificial Intelligence*, vol. 97, no. 1–2, pp. 273–324, Dec. 1997, doi: 10.1016/S0004-3702(97)00043-X.
[28] P. Paramanathan and R. Uthayakumar, "An algorithm for computing the fractal dimension of waveforms," *Applied Mathematics and Computation*, vol. 195, no. 2, pp. 598–603, Feb. 2008, doi: 10.1016/j.amc.2007.05.011.
[29] C. Gómez, Á. Mediavilla, R. Hornero, D. Abásolo, and A. Fernández, "Use of the Higuchi's fractal dimension for the analysis of MEG recordings from Alzheimer's disease patients," *Medical Engineering and Physics*, vol. 31, no. 3, pp. 306–313, Apr. 2009, doi: 10.1016/j.medengphy.2008.06.010.
[30] T. L. A. Doyle, E. L. Dugan, B. Humphries, and R. U. Newton, "Discriminating between elderly and young using a fractal dimension analysis of centre of pressure," *International Journal of Medical Sciences*, pp. 11–20, 2004, doi: 10.7150/ijms.1.11.
[31] J. Gnitecki and Z. Moussavi, "Variance fractal dimension trajectory as a tool for hear sound localization in lung sounds recordings," in *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No.03CH37439)*, 2003, pp. 2420–2423, doi: 10.1109/IEMBS.2003.1280404.

[32] L. J. Hadjileontiadis, "Wavelet-based enhancement of lung and bowel sounds using fractal dimension thresholding-Part I: methodology," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 6, pp. 1143–1148, Jun. 2005, doi: 10.1109/TBME.2005.846706.
[33] L. J. Hadjileontiadis, "Wavelet-based enhancement of lung and bowel sounds using fractal dimension thresholding-Part II: application results," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 6, pp. 1050–1064, Jun. 2005, doi: 10.1109/TBME.2005.846717.
[34] F. M. Smits, C. Porcaro, C. Cottone, A. Cancelli, P. M. Rossini, and F. Tecchio, "Electroencephalographic fractal dimension in healthy ageing and Alzheimer's disease," *Plos One*, vol. 11, no. 2, Feb. 2016, doi: 10.1371/journal.pone.0149587.
[35] R. Kohavi and D. Sommerfield, "Feature subset selection using the wrapper method: overfitting and dynamic search space topology," in *KDD*, 1995, pp. 192–197.
[36] A. Renjini, M. N. S. Swapna, V. Raj, S. Sreejyothi, and S. I. Sankararaman, "Fractal and time-series analyses based rhonchi and bronchial auscultation: a machine learning approach," *Indian Journal of Science and Technology*, vol. 15, no. 21, pp. 1041–1051, Jun. 2022, doi: 10.17485/IJST/v15i21.627.
[37] M. S. Swapna, A. Renjini, V. Raj, S. Sreejyothi, and S. Sankararaman, "Time series and fractal analyses of wheezing: a novel approach," *Physical and Engineering Sciences in Medicine*, vol. 43, no. 4, pp. 1339–1347, Dec. 2020, doi: 10.1007/s13246-020-00937-5.
[38] R. Esteller, G. Vachtsevanos, J. Echauz, and B. Lilt, "A comparison of fractal dimension algorithms using synthetic and experimental data," in *ISCAS'99. Proceedings of the 1999 IEEE International Symposium on Circuits and Systems VLSI (Cat. No.99CH36349)*, 1999, vol. 3, pp. 199–202, doi: 10.1109/ISCAS.1999.778819.

BIOGRAPHIES OF AUTHORS

Achmad Rizal received bachelor of engineering in telecommunication engineering from STT Telkom (now, Telkom University), Bandung Indonesia in 2000. He received Master degree in biomedical engineering from Institut Teknologi Bandung, Bandung, Indonesia in October 2006. Received Ph.D. degree from Universitas Gadjah Mada, Yogyakarta Indonesia. His research interests include biomedical signal processing, biomedical image processing, biomedical instrumentation, and telemedicine. Now he is associate professor in School of Electrical Engineering, Telkom University. He can be contacted at email: achmadrizal@telkomuniversity.ac.id.

Risanuri Hidayat is an associated professor in Department of Electrical Engineering and Information Technology at Universtas Gadjah Mada, Yogyakarta, Indonesia. He received Master's degree in the field of information and communication technology achieved from Agder University College in Norway in 2002. Meanwhile, the degree of Doctor obtained from King Mongkut's Institute of technology, Ladkrabang (KMITL), Thailand in 2009 in telecommunication engineering. Dr. Hidayat is the head of Digital System Lab. His research interest includes communication systems, pattern recognition and speech recognition. He can be contacted at email: risanuri@ugm.ac.id.

Hanung Adi Nugroho is an associated professor in Department of Electrical Engineering and Information Technology at Universtas Gadjah Mada, Yogyakarta, Indonesia. He received the Bachelor degree (S.T.) in electrical engineering from Universitas Gadjah Mada (UGM), Indonesia in 2001. He also received Master of Engineering degree (M.E.) in biomedical engineering from the University of Queensland (UQ), Australia in 2005. In 2012, he received his Ph.D. degree in electrical and electronic engineering from Universiti Teknologi Petronas (UTP), Malaysia. He started to join as teaching staff in the Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada (UGM) in 2002 until now. His current research interests include biomedical signal and image processing and analysis, computer vision, medical instrumentation and pattern recognition. He can be contacted at email: adinugroho@ugm.ac.id.

Willy Anugrah Cahyadi an Electrical Engineering lecturer at the School of Electrical Engineering (SEE), Telkom University, Bandung, Indonesia. He obtained his doctoral degree from the Department of Information and Communications Engineering, Pukyong National University, Busan, Korea. He received a B.Sc. in Electrical Engineering and M.Sc. in Microelectronics from Institut Teknologi Bandung (ITB), Indonesia, in 2008 and 2012, respectively. His research interests are optics, embedded systems, and healthcare instrumentation. He can be contacted at email: waczze@telkomuniversity.ac.id.