Hjorth Descriptor Measurement on Multidistance Signal Level Difference for Lung Sound Classification

A. Rizal[1, 2], R. Hidayat[2] and H. A. Nugroho[1]
[1]Departement of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia.
[2]School of Electrical Engineering, Telkom University, Bandung, Indonesia.
rizal.s3te14@mail.ugm.ac.id

***Abstract*—Biological signals have a multiscale nature; hence, many multiscale methods for biological signal analysis have been developed. One of the most popular multiscale methods is the coarse-grained procedure. The coarse-grained procedure has some drawbacks, such as a decreased variance of the signal, since the coarse-grained procedure eliminates the fast temporal scale. As such, other multiscale methods were developed to overcome the limitation of the coarse-grained procedure. In this study, we proposed a new multiscale method that preserves variance of the signal. In our proposed method, we split the signal into a new sequencing signal by using the multi-distance signal level difference (MSLD) method. In MSLD, a set of new signals emerged from the absolute value of two data samples' difference at a defined distance. To evaluate the MSLD performance, we used Hjorth descriptor as the feature extraction method in the output signal. The results were classified using multilayer perceptron (MLP). The proposed method was tested on five classes of lung sound data. The results showed that the proposed method achieved the maximum accuracy of 98.76% for the 81 data. The resulting accuracy was higher than the multiscale Hjorth descriptor using the coarse-grained procedure in our previous research. The MSLD could be combined with feature extraction methods other than Hjorth descriptor for future studies**

***Index Terms*—Hjorth Descriptor; Signal Level Difference; Lung Sound; Signal Complexity.**

I. INTRODUCTION

Lung sound is used to diagnose the abnormalities which occur in the respiratory system [1]. With the auscultation technique, lung sound is heard by the physician and analyzed to make a diagnosis. It is believed to be the most efficient method because it uses a stethoscope to gain the data [2]. This process relies heavily on the expertise and experience of the physician. With computer technology and subjectivity, the weakness in lung auscultation is insurmountable [3].

Various techniques were developed to classify lung sound automatically. Some researchers used similar methods to those used in speech signal processing, such as the Mel-frequency cepstral coefficients (MFCC) [2], [4], [5]. Meanwhile, other researchers treated lung sound like a complex signal, so signal complexity measurement methods were used to extract the characteristics [6], [7]. The most popular signal complexity measurement techniques for lung sound signal processing were entropy [8], [9], fractal dimension [10], [11] and Hjorth descriptors [12], [13]. Most of the lung sound analysis signal complexity measurements were carried out on the entire signal, not by multiscale [8], [9]. Meanwhile, Villalobos et al. tried to apply the multiscale entropy method to the feature extraction in alveolitis cases [6]. The multiscale scheme was the coarse-grained procedure proposed by Costa et al. [14]. Even if the method produces a good result, the coarse-grained procedure method has many drawbacks [15], which have been improved upon by other researchers [16], [17].

In previous studies, Hjorth descriptors were used for lung sound features extraction [12]. The accuracy result was 83.95%. Another study measured the Hjorth descriptor on a multiscale scheme by using coarse-grained procedure [13]. The accuracy result was 95.06%. From the previous research, there is still a gap to improve the accuracy since the coarse-grained procedure has drawbacks regarding the variance decreasing and occurring bias [15].

In this study, we proposed the multi-distance signal level difference Hjorth descriptor (MSLD) as a feature extraction method for lung sound classification. In this method, Hjorth descriptors were measured on the absolute of signal difference value at some specified distance. The MSLD generated relatively steady signal variance, as compared to the coarse-grained procedure. It is expected that the proposed method produces higher accuracy, as compared with Hjorth descriptor measurements on a single-scale signal or a multi-scale signal.

II. RELATED WORKS

Various digital signal processing techniques were developed for lung sound signal analysis. Lung sound signals, like other biological signals, have non-stationary and multiscale natures [6]. Most studies were extracting lung sound signal characteristics on a single scale. Sengupta et al. used empirical mode decomposition (EMD) on lung sounds and then performed heart sound detection peak on each intrinsic mode function (IMF) to reduce noise from the heart sound [4]. The Mel-frequency cepstral coefficients (MFCC) were used for further processing [4]. The results showed that the MFCC was better than the other cepstral methods like the linear prediction cepstral coefficient (LPCC). Meanwhile, Mondal, et al. used sample entropy, skewness, and kurtosis as a feature for the lung sound classification [7]. The accuracy of 92.86% was obtained for normal and abnormal lung sounds. Meanwhile, instantaneous kurtosis, discriminating function, and histogram distortion of sample entropy were used for lung sound feature extraction in [8]. A sample entropy was calculated from the sort-time Fourier transform (STFT) of lung sounds. Entropy was also used in the study conducted by Morillo, et al. [9]. Lung sounds in a chronic obstructive pulmonary disease (COPD) patient were analyzed using entropy, the mean and median frequency, spectral crest factor, entropy, relative power factor, and high order frequency moment. The accuracy of 77.6% was obtained using Fuzzy C-mean [9]. Other researchers used the fractal method for lung sound analysis. Gnitecki and Moussavi tested lung sound fractality using the Katz fractal dimension (KFD), variance fractal dimension (VFD), and Sevcik fractal dimension (SFD)[10]. The results showed that the lung sounds have fractal properties. Then, the fractal nature was used by other researchers for crackle and squawk classification on lung sounds [11]. From several studies discussed above, it can be seen that some researchers treat lung sounds like a speech signal, while other researchers use signal complexity measurements such as entropy and fractal for lung sound analysis.

Some studies have already used the multiscale scheme for lung sound analysis. Multiscale entropy (MSE) was used to analyze lung sound produced by alveolitis patients [6]. The researcher used the coarse-grained procedure with the scale of 3 and sample entropy with tolerance r = 0.1, 0.15, and 0.2 to analyze the lung sound. Compared to spectral methods, MSE produced more differences between the alveolitis patient's lung sound with healthy lung sound. In other research, the multiscale scheme was used together with the gray-level difference (GLD) [18]. Based on the result of the coarse-grained procedure signal, GLD parameters were measured for feature extraction process, using 81 lung sounds consisting of five classes of data generated with the highest accuracy of 91.36% on a scale of 1-10 based on gradient entropy as a characteristic. From the research that has been reported, multiscale analysis resulted in a higher accuracy than the signal analysis on a single scale.

In our previous study, we used Hjorth descriptor for lung sound classification [12]. An accuracy of 83.95% was obtained using MLP as a classifier. We tried to improve the accuracy by using the multiscale Hjorth descriptor with the coarse-grained procedure for multiscale schemes [13]. Using the same data and MLP as classifiers, an accuracy of 95.06% was achieved on a scale of 1-5 and complexity as a feature. In a subsequent study, we used a combination of EMD and Hjorth descriptors [19]. The resulting accuracy was 98.76% with an activity of 10 IMF as a feature. Some EMD weaknesses were found, which are the complex computation and the high influence from signal shifting [20]. In this study, we propose the MSLD method to split the signal into a sequence of new signals. MSLD maintains the signal variance and utilizes signal shifts to see the consistency of the signal.

III. Materials and Methods

The proposed lung sound classification system is shown in Figure 1. The first process was lung sound normalization; then, the MSLD process was performed at a distance of D = 1-20. Furthermore, each MSLD result calculated the Hjorth descriptors as the signal feature. The next step was the feature selection to obtain the highest accuracy with the smallest number of features. A detailed explanation of the proposed system is described in the following section.

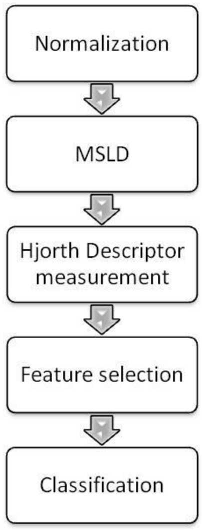

Figure 1: System design for lung sound classification using MSLD Hjorth descriptor

A. Lung Sound Data

Lung sound data were collected from various sources on the internet [21]–[23]. Some data also were taken from a CD of the textbook [24]. The collected data were converted to a wave file, and then cut into one respiratory cycle and resampled in 8000 Hz of frequency sampling. The number of lung sound data was 81, which consist of five classes. The detail is shown in Table 1. Similar data were used in previous studies [12], [13].

Table 1
Lung Sound Data

Data class	Number of data
Normal bronchial	18
Crackle	15
Asthma	13
Friction rub	15
Stridor	20

These five types of lung sound data were chosen because they represent different lung sound characteristics. Normal bronchial represents the normal lung conditions while the other classes represent the lung condition with diseases or abnormalities [3]. The normal bronchial sound is soft and can be heard on the inspiratory and the expiratory phase [1]. The crackle sound is non-musical, discontinuous, in short duration, and explosive. A crackle sound is typically associated with secretion, e.g., in bronchitis or congestive heart failure [1]. Asthma is one of the diseases that produces wheezing sounds. Wheezing sounds have the nature of musical sounds, are continuous, and have a frequency of more than 400 Hz [25]. A Stridor sound usually occurs in an upper way obstruction, which produces a loud and dominant frequency above 1000 Hz [3]. Meanwhile, friction-rub takes place in the case of pleural inflammation, and the sound characteristics are nonmusical and explosive [1].

The normalization process consists of two stages; namely, the amplitude normalization and the mean normalization. The mean normalization process was done by Equation (1) while the amplitude normalization process was done by Equation (2).

$$y(n) = x(n) - \frac{1}{N}\sum_{i=1}^{N} x(i) \tag{1}$$

$$y(n) = \frac{x(n)}{max|x(n)|} \quad (2)$$

B. Multi-distance Signal Level Difference (MSLD)

The multi-distance signal level difference (MSLD) is a modification of the gray-level difference (GLD), which is proposed by Weszka et al. [26]. GLD was calculated from the absolute value of the difference between two adjacent pixels in the horizontal, vertical, and diagonal direction. In the horizontal direction, GLD was calculated by Equation (3).

$$y(i,j) = |x(i,j) - x(i,j+D)|, \;\; D = pixel\ distance \quad (3)$$

In MSLD, because the signal used is 1D, the Equation (3) is modified into Equation (4).

$$y(i) = |x(i) - x(i+D)|, \quad D = 1,2,\ldots,K \quad (4)$$

We chose 20 as the K value, hence 20 new signals were considered as the input for the feature extraction process.

C. Hjorth Descriptor

One method for measuring the signal complexity is Hjorth descriptors [27]. The Hjorth descriptor consists of three parameters such as activity, mobility, and complexity. If the given signal x (n), where n = 1,2, ..., N then the first order variation of x (n) is $d(n) = x(n) - x(n-1)$, while the second order variation of x (n) is expressed by $g(n) = d(n) - d(n-1)$. The standard deviation of each signal sequence is expressed by Equation (5), (6), (7).

$$\sigma_0 = \sqrt{\frac{\sum_{n=1}^{N} x(n)^2}{N}} \quad (5)$$

$$\sigma_1 = \sqrt{\frac{\sum_{n=1}^{N} d(n)^2}{N}} \quad (6)$$

$$\sigma_2 = \sqrt{\frac{\sum_{n=1}^{N} g(n)^2}{N}} \quad (7)$$

From the equation above, the Hjorth descriptors parameter are calculated as follows:

$$activity = {\sigma_0}^2 \quad (8)$$

$$mobility = {\sigma_1}^2/{\sigma_0}^2 \quad (9)$$

$$complexity = \sqrt{\frac{{\sigma_2}^2}{{\sigma_1}^2} - \frac{{\sigma_1}^2}{{\sigma_0}^2}} \quad (10)$$

The three parameters were calculated on an MSLD signal results and obtained 60 features. The highest accuracy from the features was selected by reducing the distance on used MSLD.

D. Classifier and Validation

As a classifier, we used multilayer perceptron (MLP), which is a neural network with the simplest architecture consisting of three layers: the input layer, hidden layer, and output layer. The number input is equal to the number of features from the feature extraction result, while the number of the output layer is equal to the number of class classification results [28]. The present study used a varying number of hidden neurons to observe which MLP configuration produces the highest accuracy.

The MLP is a supervised learning artificial neural network (ANN). Therefore, a three-fold cross-validation (NFCV) was used as the validation process. Due to the amount of data were at least 13, the selected data of each three-fold were four to five for every dataset. The performance parameter is the accuracy value of the amount of data recognized correctly divided by the total number of data. The other parameters used are the sensitivity and specificity values.

IV. Results and Discussion

The D value used was 1-20; hence, there were 60 features. Sample results of MSLD for D = 1-5 on the normal bronchial signal is shown in Figure 2. For D = 1, the signal sample data difference is relatively small, so the generated results of MSLD has a low amplitude. The high sampling frequency of 8000 Hz makes the differences between two sequential data relatively low. When the D value is higher, the signal amplitude of the MSLD result also has a greater amplitude.

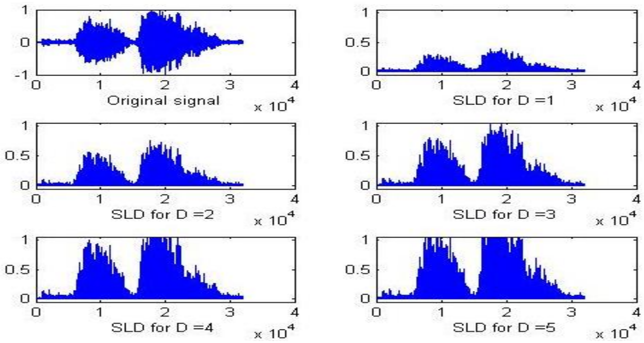

Figure 2: Normal bronchial sound and MSLD result for D =1-5

The proposed feature extraction method was tested by using the MLP with an altered number of hidden neurons and three-fold cross validation. Testing was done for the entire features (60 features) and one Hjorth descriptor parameter for D = 1-20 (20 features). The test results are shown in Figure 3.

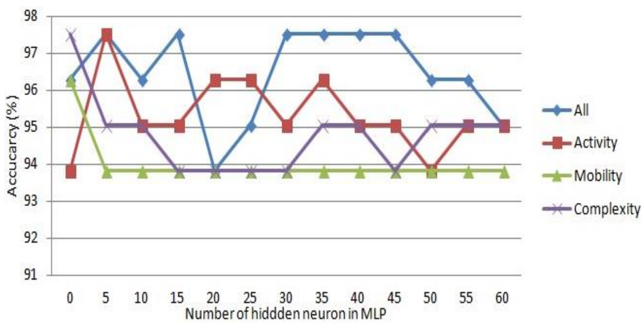

Figure 3: Effect of hidden neuron number to the accuracy

The best accuracy for the entire feature is 97.53% for the hidden neurons = 5, 15, 30, 35, 40, and 45. For the Activity feature, the best accuracy is 97.53% for the hidden neurons = 5, and hidden neurons = 0 for the Complexity feature. However, the best accuracy for mobility only reached 96.3%. Although the results for overall features are better than the activity and the complexity feature, a large number of features were used. Feature reduction was tested by using

MLP N-5-5. The obtained result is showed in Figure 4.

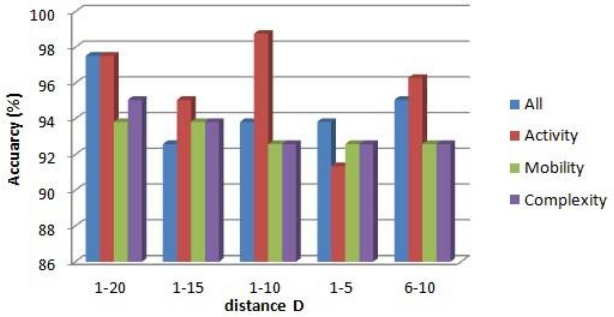

Figure 4: Effect of feature reduction by using N-5-5 MLP

Figure 4 shows that feature reduction increased the accuracy of the system. With the distance of D = 1-10, the activity feature individually produced the highest accuracy of 98.76%. Further, feature reduction (D = 1-5) decreased the accuracy of the system. An activity of D = 1-10 is considered better than D = 1-15 for a smaller number of features.

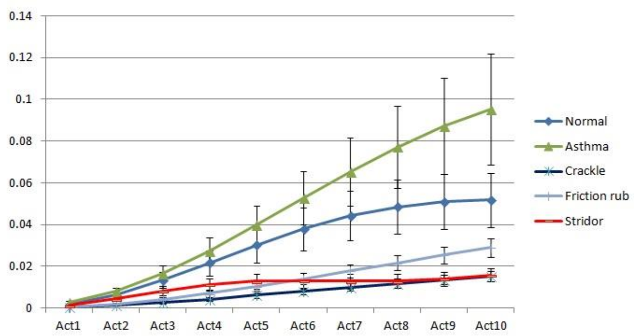

Figure 5: Mean ± std of Activity for D=1-10 for each class

Figure 5 displays the average value of activity for D = 1-10 in each data class. It shows that the greater the value D, the bigger the value of the activity will be. This result is consistent with Figure 2, which shows that the greater the value of D, the more the signal amplitude value from MSLD increases. The activity feature is mathematically the same as the signal variance: when amplitude changes rapidly, then the variance value also increases.

Table 2.
Confusion matrix for the highest accuracy

Data	Classified as				
	Bronchial	Asthma	Crackle	Friction rub	Stridor
Bronchial	18	0	0	0	0
Asthma	0	13	0	0	0
Crackle	0	0	15	0	0
Friction rub	0	0	1	14	0
Stridor	0	0	0	0	20

The classification results in the highest accuracy conditions are shown in Table 2. An error occurred in one data set; friction rub was classified as crackle. The sensitivity value of friction rub became 93.33%, while the specificity value of crackle was 98.45%.

In general, the proposed method performed better than the Hjorth descriptor measurement signal on the entire signal and the multiscale scheme by using a coarse-grained procedure [12], [13].

The comparison between single-scale, multiscale, EMD, and MSLD Hjorth descriptors are described in Table 3.

Table 3.
Comparison of features and accuracy with previous research

	Original features			
	Single scale	Multiscale	EMD	MSLD
Reference	[12]	[13]	[19]	Proposed method
Number of data	81	81	81	81
Scale	1	20	10	20
MLP configuration	3-45-5	60-15-5	20-35-5	60-5-5
Number of features	3	60	30	60
Feature used	Activity, Mobility, Complexity	Activity, Mobility, Complexity	Activity, Mobility, Complexity	Activity, Mobility, Complexity
Accuracy	83.95%	90.12%	96.3%	97.53%
	Feature reduction			
Scale	1	5	10	10
MLP configuration	3-45-5	5-15-5	10-25-5	10-5-5
Number of features	3	5	10	10
Feature used	Activity, Mobility, Complexity	Complexity	Activity	Activity
Accuracy	83.95%	95.06%	98.76%	98.76%

The Hjorth descriptor measurement for the entire signal produced three signal features, and the maximum accuracy was 83.95%. We could not reduce the number of features because it would decrease the accuracy [12]. Meanwhile, on the multiscale Hjorth descriptor, feature reduction improves the accuracy to 95.06% with five number features, and the complexity becomes the dominant feature [13].

The coarse-grained procedure used in multiscale Hjorth descriptors, as used in multiscale entropy, are expressed as the Equation (11) [14],

$$y_j^{(\tau)} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} x_i \quad , \quad 1 \le j \le \frac{N}{\tau} \qquad (11)$$

where $x_i$is is the input signal while $y_j^{(\tau)}$ is the output signal on a scale τ. The output signal $y_j^{(\tau)}$on a scale τ is equal to the average of τ sequence number data samples of the signal x. This method has many disadvantages that many methods were developed to fix, such as composite multiscale entropy (CMSE) [17] or modified multiscale entropy (MMSE) [16]. One drawback of the coarse-grained procedure is that the signal variance value is decreased, which produces bias in the calculation parameters of the signal on the following scale [15]. Comparison of the variance in the coarse-grained and MSLD procedures is shown in Figure 6.

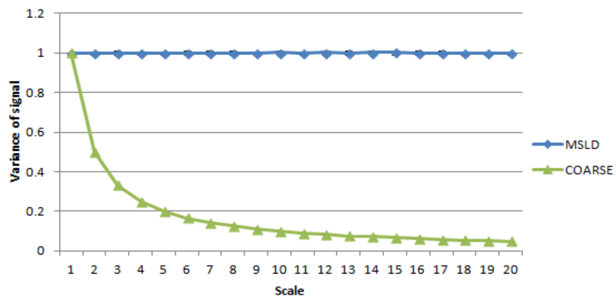

Figure 6: Comparison of variance value for MSLD and the coarse-grained procedure

The variance of the signal was measured at random along the 30,000 samples with initial variance value = 1. It can be seen that the variance of the signal using the coarse-grained procedure decreases with an increase in scale while the variance of MSLD is relatively fixed.

MSLD Hjorth descriptor produced the same accuracy with the EMD-Hjorth descriptor. Due to computation complexity and signal shifting effect as aforementioned, EMD did not become our choice. MSLD Hjorth descriptor generates higher accuracy compared with the multiscale Hjorth descriptor, and feature reduction improves the accuracy to 98.76%. Compared with multiscale Hjorth descriptor, MSLD Hjorth descriptor needs more features to produce the maximum accuracy. MSLD method can be used to measure other parameters and provides an overview of coexistence of two data samples at a certain distance. Consistency signals can be tested as measured by a series of a predetermined distance. The data cutting effect, the signal shifting, and the frequency sampling at MSLD were not tested in this study. They can be another interest for future studies.

V. Conclusion

This paper presented the classification concern of lung sounds by using MSLD Hjorth descriptor. The use of MSLD on the Hjorth descriptor measurement can improve the accuracy of lung sound classifications. One of MSLD advantages is a simple computation by counting the absolute value of the difference sample data signal at a certain distance. The number of features used less; hence, less computation time is needed. In the present study, the features reduction is used to reduce the amount of distance by using a single parameter of Hjorth descriptor. In a future study, a better feature selection method can be employed to obtain distance and Hjorth descriptors parameter combination to produce maximum accuracy

Acknowledgment

This research was funded by PPI grant (Penyiapan Publikasi Internasional) 2016, Faculty of Engineering, Universitas Gadjahmada no: 4341/H1.17/PL/2016.

References

[1] A. Bohadana, G. Izbicki, and S. S. Kraman, “Fundamentals of lung auscultation.,” *N. Engl. J. Med.*, vol. 370, no. 8, pp. 744–51, Feb. 2014.

[2] C. Chen, W. Huang, T. Tan, C.-C. Chang, and Y. Chang, “Using K-Nearest Neighbor Classification to Diagnose Abnormal Lung Sounds,” *Sensors*, vol. 15, no. 6, pp. 13132–13158, Jun. 2015.

[3] A. Kandaswamy, C. S. Kumar, R. P. Ramanathan, S. Jayaraman, and N. Malmurugan, “Neural classification of lung sounds using wavelet coefficients.,” *Comput. Biol. Med.*, vol. 34, no. 6, pp. 523–37, Sep. 2004.

[4] N. Sengupta, M. Sahidullah, and G. Saha, “Lung sound classification using cepstral-based statistical features,” *Comput. Biol. Med.*, vol. 75, pp. 118–129, Aug. 2016.

[5] B. Wang, L. Miao, H. Dong, and Z. Zheng, “The Research of Lung Sound Signals Based on Cepstrum Analysis,” in *2012 International Conference on Biomedical Engineering and Biotechnology*, 2012, no. 61102014, pp. 934–938.

[6] S. Charleston-Villalobos, L. Albuerne-Sanchez, and R. Gonzalez-Camarena, “Linear and Nonlinear Analysis of Base Lung Sound in Extrinsic Allergic Alveolitis Patients in Comparison to Healthy Subjects,” *Methods Inf Med*, vol. 52, pp. 266–276, 2013.

[7] A. Mondal, P. Bhattacharya, and G. Saha, “Detection of lungs status using morphological complexities of respiratory sounds.,” *Sci. World J.*, vol. 2014, pp. 1829–38, Jan. 2014.

[8] F. Jin, F. Sattar, and D. Y. T. Goh, “New approaches for spectro-temporal feature extraction with applications to respiratory sound classification,” *Neurocomputing*, vol. 123, pp. 362–371, Jan. 2014.

[9] D. S. Morillo, A. L. Jiménez, and S. A. Moreno, “Computer-aided diagnosis of pneumonia in patients with chronic obstructive pulmonary disease,” *J. Am. Med. Informatics Assoc.*, vol. 20, no. e1, pp. e111--e117, 2013.

[10] J. Gnitecki and Z. Moussavi, “The fractality of lung sounds: A comparison of three waveform fractal dimension algorithms,” *Chaos, Solitons & Fractals*, vol. 26, no. 4, pp. 1065–1072, Nov. 2005.

[11] L. J. Hadjileontiadis, “A texture-based classification of crackles and squawks using lacunarity.,” *IEEE Trans. Biomed. Eng.*, vol. 56, no. 3, pp. 718–32, Mar. 2009.

[12] A. Rizal, R. Hidayat, and H. A. Nugroho, “Determining Lung Sound Characterization Using Hjorth Descriptor,” in *2015 International Conference on Control, Electronics, Renewable Energy and Communication (ICCEREC)*, 2015, pp. 20–23.

[13] A. Rizal, R. Hidayat, and H. A. Nugroho, “Multiscale Hjorth Descriptor for Lung Sound Classification,” in *International Conference on Science and Technology 2015*, 2015, vol. 160008, pp. 1–7.

[14] M. Costa, A. L. Goldberger, and C.-K. Peng, “Multiscale entropy analysis of complex physiologic time series.,” *Phys. Rev. Lett.*, vol. 89, no. 6, p. 68102, 2002.

[15] A. Humeau-heurtier, “The Multiscale Entropy Algorithm and Its Variants: A Review,” *Entropy*, vol. 17, pp. 3110–3123, 2015.

[16] S. Wu, C. Wu, K. Lee, and S. Lin, “Modified multiscale entropy for short-term time series analysis,” *Physica A*, vol. 392, no. 23, pp. 5865–5873, 2013.

[17] S. Wu, C. Wu, S. Lin, C. Wang, and K. Lee, “Time Series Analysis Using Composite Multiscale Entropy,” *Entropy*, vol. 15, pp. 1069–1084, 2013.

[18] A. Rizal, R. Hidayat, and H. A. Nugroho, “Multi-scale Grey-Level Difference for Lung Sound Classification,” *J. Electr. Syst.*, vol. 13, no. 3, pp. 556–564, 2016.

[19] A. Rizal, R. Hidayat, and H. A. Nugroho, “Lung Sound Classification Using Empirical Mode Decomposition and the Hjorth Descriptor,” *Am. J. Appl. Sci.*, to be published

[20] G. Rilling, P. Flandrin, and G. Paulo, “On Empirical Mode Decomposition and Its Algorithms,” in *IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing NSIP-03*, 2003.

[21] “The R.A.L.E Repository.” [Online]. Available: http://www.rale.ca/Repository.htm. [Accessed: 22-Jul-2015].

[22] D. Arnall, “Breath Sounds.” [Online]. Available: http://jan.ucc.nau.edu/~daa/heartlung/breathsounds/contents.html. [Accessed: 01-May-2015].

[23] “The Auscultation Assistant - Breath Sounds.” [Online]. Available: http://www.med.ucla.edu/wilkes/lungintro.htm. [Accessed: 01-Jun-2015].

[24] R. L. Wilkins, J. E. Hodgkin, and B. Lopez, *Lung Sounds: A Practical Guide with Audio CD*, 2nd ed. Mosby, 1996.

[25] S. Reichert, R. Gass, C. Brandt, and E. Andrès, “Analysis of Respiratory Sounds : State of the Art,” *Clin. Med. Circ. Respirat. Pulm. Med.*, vol. 2, pp. 45–58, 2008.

[26] J. S. Weszka, C. R. Dyer, and A. Rosenfeld, “A Comparative Study of Texture Measures for Terrain Classification,” *Syst. Man Cybern. IEEE Trans.*, vol. SMC-6, no. 2, pp. 269–285, 1976.

[27] B. Hjorth, “EEG analysis based on time domain properties,” *Clin. Neurophysiol.*, vol. 29, no. 3, pp. 306–310, 1970.

[28] F. Albu, A. Mateescu, and N. Dumitriu, “Architecture Selection for a Multilayer Feedforward Network,” in *International Conference on Microelectronics and Computer Science*, 1997, pp. 131–134.