Lung Sound Recognition Using Wavelet Packet Decomposition and ART2 (Adaptive Resonance Theory 2) Neural Network

Achmad Rizal[1], Tati L R Mengko[2], Andriyan B Suksmono[3]
[1)] Electrical Engineering Department , STT Telkom Bandung
Jl Telekomunikasi Bojong Soang, Bandung , phone : +62 21 7270036
[1,2,3)] Biomedical Engineering Program, Insitut Teknologi Bandung
Jl Ganesha 10, Bandung phone: +62 22 2534117
[1]arz@stttelkom.ac.id

Abstract

Usually, physicians diagnosing lung diseases by listening to the lung sound using stethoscope. This technique is known as auscultation. Some lung diseases produce unique lung sounds, which is refers to special recognized pattern. But the main problems are the the frequency of lung sounds that are low (20 – 2000 Hz), low amplitude, interference from other sounds, ear sensitiveness, and low variety of the pattern of lung sounds that are almost similar. These factors remain to the false diagnosing of lung disease if the auscultation procedures aren't conducted correctly.

*Actually, false diagnoses can be minimized by a software that can classify lung sounds automatically. Input for the software are recorded lung sounds in *.wav, mono, and sampling frequency of 8000 Hz, with one respiration cycle. Lung sounds recognition is built base on wavelet analysis. Also, lung sounds are decomposed using wavelet packet up to 5 levels. The decomposition scenario includes breaking down lung sound frequency into 125 Hz for areas below 1000 Hz, 250 Hz for range areas of 1000-2000 Hz, and 500 Hz for range areas of 2000-3000 Hz. The areas which are ranging from 3000 Hz up to 4000 Hz isn't divided with another frequency because lung sounds usually don't belong to this frequency. The signal energy in each subband is counted to produce feature of the lung sound. There are 15 feature signals, and those would be recognized using neural network.*

The result of the test on lung sound recognition system that has been developed shows that accuracy can be achieved up to 86%, for coifflet1 and parameters of ART neural network: ρ=0.999, alpha=0.1, iteration=3. By the result of the test, the lung recognition system can be applied for educational and medical purpose.

Keywords: Lung sound, auscultation, wavelet packet decomposition, neural network, ART2.

1. Introduction

The respiratory system can be separated into two tracts (upper and lower) The upper respiratory tract is comprised of the nose, paranasal sinuses, pharynx, and the larynx. The purpose of this tract is to purify, warm, and humidify ambient air before it reaches the gas exchange units. The lower respiratory tract begins with the trachea, the right main bronchus which divides into three lobar or divisions of the lung (upper, middle, and lower), the left main bronchus which divides into two lobes (upper and lower), followed by the bronchioles, and terminating at the alveoli (air sacs) which form the gas exchange surface [14].

Lung sound are generated by turbulent airflow through the respiratory tree.[10]. The turbulence happen when air flow from wider air cavity to narrower cair cavity and vice versa. Generally, lung sounds are classified into 3 groups, normal lung sound, abnormal and adventitious sounds. The sounds separated into some catagories based on pitch, intensity, location and inspiration-expiration ratio[10]. Normal lung sounds are classified as tracheal, bronchial, bronchovesicular and vesikular sound.

Tracheal breath sounds are high-pitched and loud, with a harsh and hollow (or "tubular) quality. The inspiratory and expiratory phases are of equal duration, and there is a definite pause between phases. Tracheal breath sounds usually have very little clinical usefulness. Bronchial sounds normally heard over the upper manubrium, these breath sounds directly reflect turbulent airflow in the main-stem bronchi. They are loud and high-pitched but not quite as harsh and hollow as tracheal breath sounds, the expiratory phase is generally longer than the inspiratory phase, and there is usually a pause between the phases. If bronchial sounds heard over the thorax suggest lung consolidation and pulmonary disease. Pulmonary consolidation results in improved transmission of breath sounds originating in the trachea and primary bronchi that are then heard at increased intensity over the thorax.

Bronchovesicular sounds are normally heard in the anterior first and second intercostal spaces and posteriorly between the scapulas, where the main-stem bronchi lie. The inspiratory and expiratory phases are about equal in duration, with no pause between phases. Bronchovesicular sounds are soft and less harsh than bronchial breath sounds and have a higher pitch than vesicular sounds. Vesicular sound audible over peripheral lung fields, these breath sounds are soft and low-pitched, without the harsh, tubular quality of bronchial and tracheal breath sounds. The inspiratory phase is about three times longer than the expiratory, with no pause between phases.

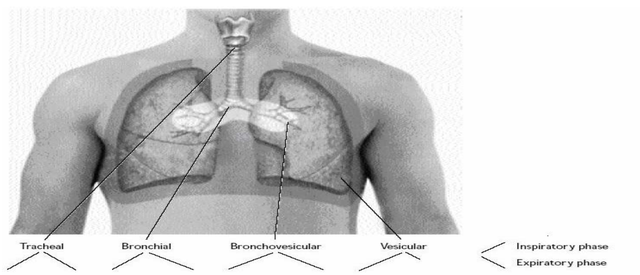

Figure 1. Location of normal breath sound

Breath sounds are considered abnormal if they are heard outside their usual location in the chest or if they are qualitatively different from normal breath sounds (e.g. decreased or absent). They are divided into two categories: (1) continuous and (2) non-continuous lung sounds. The continuous adventitious lung sounds such as wheezes, and discontinuous adventitious lung sound are classified as crackle and pleural rub. All the sounds indicate condition of lung.

2. Method

The aim of this research is to design a lung sound recognition system that able to recognize lung sound automatically. Figure 2 shows the simplified block diagram of the system.

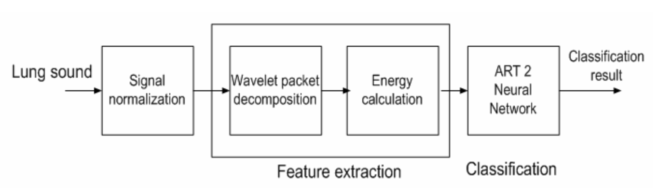

Figure 2. Simplified block diagram of the system

Data

Input data for this system is recorded lung sound in *.wav, mono, sampling frequency at 8000 Hz. The data are collected from many resources in internet [4][5][6][7][8][10][11], then cutted into 1 respiration cycle. The data consisted of 28 class (324 data) dan generally classified into normal sound, crackle, wheezing, grunting, ronchi and pleural rub.

Signal Normalization

In order to make the signal has the same amplitude and remove the DC component, signal normalization is done. DC component removal is defined as follow.

$$S(i) = S(i) - \frac{1}{N}\sum_{i=1}^{N} S(i) \qquad (1)$$

where S(i) is the input signal in time domain. The next step is amplitude normalization. This process makes the maximum amplitude of signal become 1.

$$S(i) = \frac{S(i)}{S\ \max} \qquad (2)$$

Wavelet Packet Decomposition

The wavelet packet method is a generalization of wavelet decomposition that offers a richer signal analysis. In the orthogonal wavelet decomposition procedure, the generic step splits the approximation coefficients into two parts. After splitting we obtain a vector of approximation coefficients and a vector of detail coefficients, both at a coarser scale. The information lost between two successive approximations is captured in the detail coefficients. Then the next step consists of splitting the new approximation coefficient vector; successive details are never reanalyzed. In the corresponding wavelet packet situation, each detail coefficient vector is also decomposed into two parts using the same approach as in approximation vector splitting. This offers the richest analysis: the complete binary tree is produced as shown in the following figure.

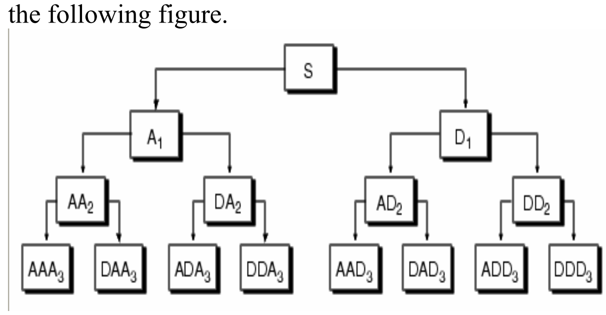

Figure 3. Wavelet packet decomposition tree at level 3

The decomposition scenario includes breaking down lung sound frequency into 125 Hz for areas below 1000 Hz, 250 Hz for range areas of 1000-2000 Hz, and 500 Hz for range areas of 2000-3000 Hz. The areas which are ranging from 3000 Hz up to 4000 Hz isn't divided with another frequency because lung sounds usually don't belong to this frequency. Figure 4 shows the decomposition of the signal.

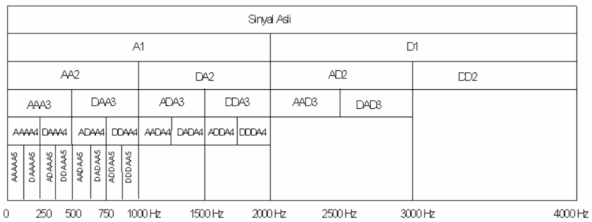

Figure 4 Wavelet Packet Decomposition Scheme

Signal energy of each subband becomes the input vector for neural network in next stage.

ART2 Neural Network

ART2 (Adaptive Resonance Theory 2) is ART1 architecture improvement. These networks have differences in input data type at F1 layer. In ART1, input for layer F1 has binary value but ART2 input vector for F1 layer have continuous value[2]. ART 2 has modification method on input vector to accommodate continuous pattern. Because of the input vector has continuous value, that might has closed value, ART2 F1 layer architecture is more complicated than ART1. F1 layer in ART2 contains combination of normalization and noise reduction mechanism. The process need a reset mechanism to compare top-down signals and button-up signals. Figure 5 shows the architecture of ART2 neural network.

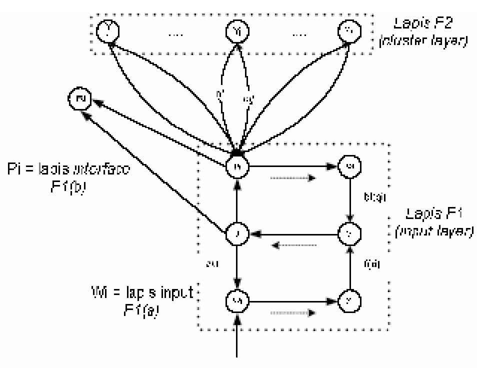

Figure 5. ART 2 Architecture [2]

F layer consist of 6 types of input unit : W,X,P,U,V and Q. Each unit consists of n unit that shows dimension of input pattern. Symbols and connection between units in F1 layer show the transformation that moving from one unit to another unit, it doesn't show multiplication for given value. Except for relation of Pi unit which is in F1 layer that shows multiplication weight of each transmitted signal between them.

F2 unit activation which become winner is d, where 1< d < 1. The activation function is applied on p vector and x vector concise with training algorithm. The symbol shows normalization process.

Competition occurs in F2 layer. Every unit Yi compete and winner-take-all, it means that the winner gets the learning process for each input unit from Pi in F1 layer. Learning process occurs only if the vector weight in up-down direction has sufficient similarity with the input vector. Activation function is given to input units from *Xi* (*f(xi)*) and unit *Qi* (*bf(qi)*). The activation unit acts to control some components of activation vectors which lay in lower stage which is chosen by user. Meanwhile in connection between W to U and from Q and V have fix value a and b.

3. Results and Discussion

Signal Normalization Result

Figure 6 and figure 7 show signal and spectra examples for bronchial and pleural rub, and normalization results.

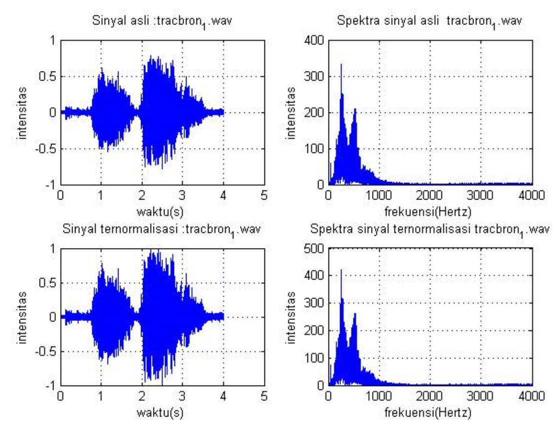

Figure 6. Bronchial Sound

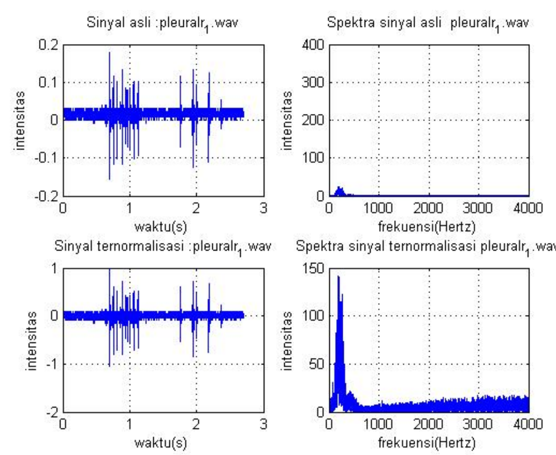

Figure 7. Pleural Rub Sound

Figure 6 shows that bronchial sound has little DC component. It makes the normalization result just effect to amplitude of the signal. Figure 7 shows that pleural rub sound has significant DC component, so normalization process effect to signal amplitude and spectral.

Wavelet Packet Decomposition Feature Extraction

For the next step, the signal is extracted by wavelet packet decomposition. Daubechies 2 was chosen as mother wavelet. The process produces 15 features for each data. Figure 8 shows the pattern of ART2 input vector for bronchial sound.

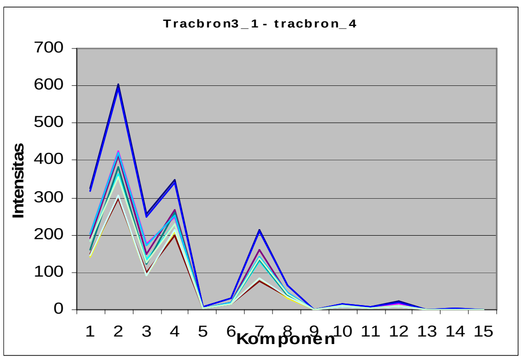

Figure 8. Bronchial Sound Features

Analysis of ART 2 Neural Network Recognition

Experiment was conducted by changing ART2 parameter after each training session. ART2 parameter which produces the highest accuracy was chosen for next stage experiment. Accuracy is defined as follow:

$$\text{Accuracy} = \frac{\sum \text{correct recognition}}{\text{Total data}} x100\% \qquad (3)$$

Correct recognition based on assumption active neuron definition. Each data will activate neuron and one class data shall activate one or more neuron. The most data class which is recognized in the neuron will be the neuron definition. So, another data class in the neuron will cause wrong recognition.

ART2 neural network was tested to recognized lung sound data with parameters which is showed by table 1.

Table 1. ART2 Neural Network Parameters

A	=	10	θ	=	0.02
B	=	10	α	=	0.1
C	=	0.1	ρ	=	0.99 - 0.999
D	=	0.9	Iteration	=	1-4
e	=	0.0000001			

By changing ρ (rho) parameter which is vigilance parameter, the experiment result is shown by table 2.

Table 2 ρ (rho) Effect to Network Performance

ρ	Active Neuron	Accuracy (%)
0.99	26	64.51
0.992	29	63.27
0.994	34	69.44
0.996	45	79.94
0.998	53	82.72
0.999	66	83.02

Vigilance parameter (ρ) effect the sensitivity of the network in order to response difference between one data to another. Usually ρ (rho) was set 0.7 – 1. If ρ was set below 0.7, network will be unsensitive to the data, it will make the network won't activate new neuron. If ρ = 1, every input data will make network creates new neuron. The experiment result shows the optimum value was reached by setting the vigilance parameter = 0.999. At this condition, accurary of the system reachs is about 83%.

Effect of iteration on system performance was shown by table 3. Larger iteration value will increase network sensitivity. At iteration = 4, system accurary reach 90% with 165 activated neuron for 324 data. It means that at average, 1 neuron will recognize 2 datas. In this condition network is too sensitive. Iteration =3 was chosen for this system.

Table 3 Iteration Effect to Network Activation

Iteration	Active Neuron	Accuracy (%)
1	24	66.67
2	33	71.30
3	66	83.02
4	165	94.14

Effect of learning rate (alpha) on system performance was shown by table 4. Larger learning rate value will increase network sensitivity. At alpha = 0.4, system accurary reach 95.99% with 180 activated neuron for 324 data. It means that at average, 1 neuron will recognize 2 datas. In this condition network is too sensitive. Learning rate at 0.1 will make the network at optimum performance. Accurary is still high (about 83%) but active neuron isn't too much. Learning rate 0.1 will cause network in slow learning condition, it will keep network not too sensitive. Learning rate must be kept low because vigilance parameter quite high (0.999). The Balance between vigilance parameter and learning rate will optimize recognition result of the network.

The advantages of proposed method are simple computation, time unvarying, and flexibility to set network sensitivity. Wavelet packet method doesn't need uniform sample length data, so it easy to record data directly with different time recording.

Table 4 Learning Rate Effect to Network Activation

alpha	Active neuron	Accuracy (%)
0.05	40	69.14
0.1	66	83.02
0.2	111	83.02
0.4	180	95.99

Wavelet packet decomposition method depends on sampling frequency choice. Different sampling frequency with same decomposition scheme will produce different subband. This method also depends on mother wavelet choice that will produce different input pattern. Further works will investigate mother wavelet choice effect to system performance.

4. Conclusion

The experimental results demonstrate the proposed feature extraction methods (wavelet packet decomposition and ART2 neural network) have encouraging recognition performance. Accuracy of the system is about 83%. Further research is needed to improve performance of the lung sound recognition system.

References

1. Burrus, C Sidney, and Gopinath, *Introduction to Wavelet and Wavelet Transform*, Prentice Hall International, 1998
2. Carpenter G.A. y Grossberg S, *ART2: Self-organizing of stable category recognition codes for analog input pattern*. Applied Optics, Vol. 16, N 23, December. 1987
3. Freeman, James A. and Skapura, David M. *Neural Networks; Algorithms, Applications, and Progamming Techniques*. Addison-Wesley Publishing Company, Inc. 1997.
4. http://www.medstudents.com.br/pneumo/lungsounds/lungsou.htm
5. http://www.umshp.org/rt/sounds/sounds.html
6. http://www.uinet.or.jp/~ishiyasu/index_en.html
7. http://www.wilkes.med.ucla.edu/lungintro.htm
8. http://www.rale.ca/Repository.htm
9. http://www.wavelet.org
10. http://sprojects.mmi.mcgill.ca/mvs/mvsteth.htm
11. http://www.acoustics.org/press/132nd/2aea4.html
12. http://www.mathworks.com
13. Hudson, Donna L, and Cohen, Maurice E, *Neural Networks and Artificial Intelligence for Biomedical Engineering* , IEEE Press. 1999
14. Kaelin, Mark, *Auscultation: Listening to Determine Dysfunction* . Professionalization of Exercise Physiology online, An international electronic journal for exercise physiologists. ISSN 1099-5862, Vol 4 No 8 August, 2001
15. medocs.ucdavis.edu/IMD/420C/sounds/lngsound.htm
16. Polikar, Roby. (1996). *The Wavelet Tutorial*, Iowa State University, Ames, USA, www.wavelets.com
17. Walker, James S,. *Wavelet and Their Scientific Applications*, CRC Press, 1999
18. Zahra, Moussavi, Mary T Leopando, et al . *Computerized Acoustical Respiratory Phase Detection without Airflow Measurement,* Medical & Biological Eng. & Comp, Vol 38 (2) : 198:203. 2000