Multilevel Wavelet Packet Entropy: A New Strategy for Lung Sound Feature Extraction Based on Wavelet Entropy

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***Abstract*— Wavelet packet entropy (WPE) is one of the entropy measurement methods based on wavelet transform. If wavelet entropy (WE) is used in discrete wavelet transform (DWT), then WPE used wavelet packet decomposition (WPD) for entropy calculation. Various entropy measurement techniques are used in WPE calculations and generate 2^N parameters where N refers to the decomposition level. In this paper, we proposed a new method based on WPE called multilevel wavelet packet entropy (MWPE). With the proposed method, the number of parameters produced is N, the wavelet decomposition level. The accuracy up to 97.98% was obtained for five classes of lung sound. The proposed method yielded accuracy higher than the use of one decomposition level in WPE. This method can also be used for the features extraction of the biological signals such as electrocardiogram (ECG), or electroencephalogram (EEG).**

Keywords— *wavelet entropy, wavelet packet entropy, decomposition level, lung sound, classification*

I. Introduction

The pulmonary sound is one of the biological signals that contain information about the health of the respiratory system. Various methods have been developed to improve the accuracy of pulmonary sound detection using the digital signal processing techniques. The lung sound spectral density or lung sound amplitude can be analyzed using various methods [1]. The exploration of digital signal processing method aims to overcome the weaknesses of auscultation techniques that are still the main technique in diagnosing lung sound [1].

One of the quite popular methods in lung sound analysis is wavelet analysis. Some researchers used discrete wavelet transform (DWT) to decompose lung sounds [2], [3] while other used wavelet packet decomposition (WPD) [4]. Various wavelet-based methods for features extraction have been developed for biological signal analysis. In [5], wavelet entropy was used for brain signal (EEG) analysis. It is an entropy measurement using subband produced by discrete wavelet transform (DWT). Safara et al. used wavelet packet decomposition (WPD) and calculated the entropy of each subband for murmur analysis on heart sound [6]. Another variation of entropy measurement on WPD is the usage of other entropy such as sample entropy on wavelet subband [7], Tsallis wavelet entropy [8], or normalized Shannon wavelet entropy [9].

Another wavelet-based method is wavelet packet entropy (WPE), several variations of which have been proposed by some researchers. In [6], entropy was computed using crest energy on the sub-band of WPD while in [10] Shannon entropy was counted in WPD's sub-bands. The number of the generated feature is 2^N where N refers to the signal decomposition level. In this research, we proposed a new method based on WPE called as multilevel wavelet packet entropy (MWPE). Compared to other WPEs, MWPE produced a smaller number of features. In the proposed method, Shannon entropy was calculated using all sub-bands of WPD results as in WE at the decomposition level 1 to N. Then, the entropy of WPD for all decomposition levels was used as the features. Thus, a reduction in the number of features from 2^N to N could occur. In this paper, we showed that the usage of MWPE could produce a higher accuracy compared to the usage of a single level of WPE.

The rest of this paper is organized as follows. In Section 2, we provided the background theory of WE and. The details of processes are explained in Section 3. The results of classification through generated features are presented in Section 4. Conclusions and potential application is given in Section 5.

II. Wavelet Entropy and Wavelet Packet Entropy

Discrete wavelet transform (DWT) for any signal S(t) can be expressed as [11]:

$$(W_\psi S)(j,k) = \int_{-\infty}^{+\infty} S(t)\psi_{j,k}(t)dt, \quad (1)$$

where $\psi_{j,k}(t)$ is discrete mother wavelet function, j and k are the scale and translation parameter respectively with $j \neq 0$.

If given wavelet coefficient $C_j(k) = \langle S, \psi_{j,k} \rangle$ produced by DWT, then the energy of the signal on scale $j = 1, 2, \ldots, N$ is expressed as:

$$E_j = \sum_k |C_j(k)|^2 \quad (2)$$

The total energy of the signal which is produced by DWT can be stated as:

$$E_{tot} = \|S\|^2 = \sum_j \sum_k |C_j(k)|^2 = \sum_j E_j \quad (3)$$

Relative wavelet energy for scale j is considered as

$$P_j = \frac{E_j}{E_{tot}} \quad (4)$$

Then wavelet entropy (WE) can be defined as [5]

$$WE = -\sum p_i \ln p_i \quad (5)$$

If WE was produced by DWT, then another entropy can be developed from the calculation of wavelet packet decomposition (WPD). If at DWT, only approximation components are further decomposed, then in WPD, decomposition is performed on the component approximation and detail components as shown in Fig 1.

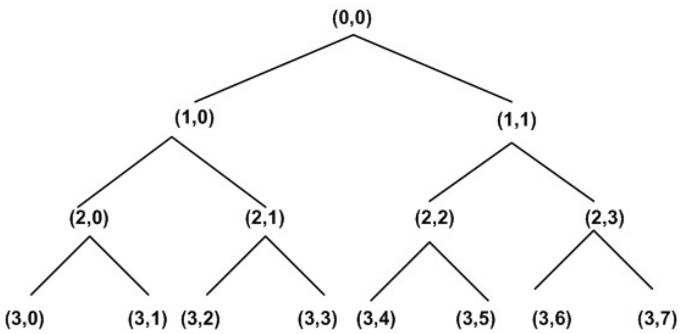

Fig. 1. Tree diagram of WPD with level decomposition of 3

DWT for level decomposition of 3 only produce (3,0), (3,1), (2,1) and (1,1) which called as A3, D3, D2, and D1 respectively. Meanwhile, WPD produces all the node in the tree.

WPD on signal S(t) can be defined as:

$$d_{j,n}(k) = 2^{\frac{j}{2}} \int_{-\infty}^{+\infty} S(t)\psi_n(2^{-j}t - k)dt,$$

$$0 \leq n \leq 2^N - 1 \quad (6)$$

where S(t) is an original signal, j is scale, n and k are band and surge parameter respectively. From (6) we can compute the energy of each sub-band as:

$$E_{j,n} = \sum_k |d_{j,n}(k)|^2 \quad (7)$$

where j, n, and k represent the scale, band, and surge parameter respectively. The total energy of WPD is:

$$E_{tot} = \sum_n E_{j,n} \quad (8)$$

Using the same way with (4), relative energy for each sub-band in scale j can be expressed as:

$$p_{j,n} = \frac{E_{j,n}}{E_{tot}} \quad (9)$$

Thus, WE of the WPD process can be called as wavelet packet entropy (WPE) and expressed as:

$$WPE = -\sum p_{j,n} \ln p_{j,n} \quad (10)$$

In this paper, we proposed multilevel wavelet packet entropy (MWPE) expressed as WPE_N^j, where j = 1,…, N, and N is decomposition level. Thus, in MWPE level N will produce:

$$MWPE_N = [WPE_N^1, WPE_N^2, \ldots, WPE_N^N] \quad (11)$$

In previous studies, commonly only one WPE value was used as a feature for a signal analysis. In this paper, it is proposed to use N WPE for the feature extraction of the pulmonary sound signal to improve accuracy in pulmonary sound classification.

III. Materials and Methods

The process of lung sound classification includes several processes as shown in Figure 2. The process consists of preprocessing, WPD, entropy calculation, and classification. The details of each process will be explained in the following subsections.

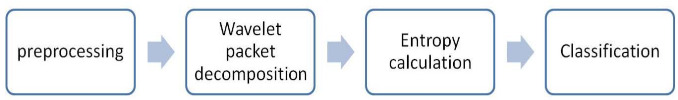

Fig. 2. Block diagram of system

A. Lung Sound Data

The lung sound data is 99 comprising 22 normal sound data and 77 abnormal sound data (composing 18 wheeze sounds, 21 crackle sound, 18 pleural rubs, and 20 stridors). The data was taken from several sources on the internet as well as offline sources [12]–[15]. The same data was used in previous research [4], [16], [17]. The data consisted of one respiratory sound cycle and recorded with a sampling frequency of 8000 Hz. The length of each data was 16000-32000 samples. In each data, we made a preprocessing step consisting of DC component removal and amplitude normalization as in (12) and (13).

$$y(n) = x(n) - \frac{1}{N}\sum_{N} x(n) \tag{12}$$

$$y(n) = \frac{x(n)}{max|x|} \tag{13}$$

where x (n) is the input signal, and y (n) is the output signal. This process aims to equalize the signal amplitude due to some different recording processes.

B. *WPD and Entropy Measurement*

In the WPD process, we used Haar wavelet, Daubechies2 (Db2), Daubechies8, Biorthogonal1.5 (Bior1.5), and Biorthogonal2.8 (Bior2.8) as mother wavelet. WPD level 7 was used to decompose the pulmonary sound signal because at that level the width of the sub-band was quite narrow about 31.25Hz. Mother wavelets and level 7 were selected to produce the best accuracy in previous studies [2]–[4]. For the feature extraction, we used WPE at one level of decomposition and $MWPE_N$ as a comparison.

C. *Classification*

We used multilayer perceptron (MLP) as the classifier. MLP is one form of artificial neural network (ANN), which consists of the input layer, hidden layer, and an output layer. The number of nodes in the input layer is equal to the number of features used; while the number of output layers is equal to the number of classes to be classified. The number of hidden layers and nodes in hidden layers tailored to the needs. In this study, one hidden layer was used.

Since MLP is included in supervised learning of ANN, it is necessary to divide the training data and test data. For this, 3fold cross-validation (3fold CV) [18] was used. At 3fold CV, the data was split into three datasets. Two datasets were used as training data, and the rest was used as test data. This process was repeated until all datasets have been used as test data. The performance parameter used was accuracy, i.e., the amount of data correctly classified.

IV. Result and Discussion

Figure 3 and Fig 4. show the plot of stridor and pleural rub sound in the time and frequency domain respectively. Meanwhile, the feature of the MWPE order of 7 ($MWPE_7$) in each lung sound class is displayed in Fig. 5.

Figure 5 shows that stridor produced the highest WPE_N^j compared to other sounds, while pleural rub produced the smallest WPE_N^j. As shown in Figure 3, the stridor spectrum tended to be more evenly distributed across the entire frequency range while the pleural rub spectrum was concentrated at a frequency of about 200Hz. If the energy in each wavelet subband tended to be evenly distributed, then the WPE_N^j value would tend to be large. In contrast, if the energy was concentrated only on one sub-band, then WPE_N^j would be relatively small [11].

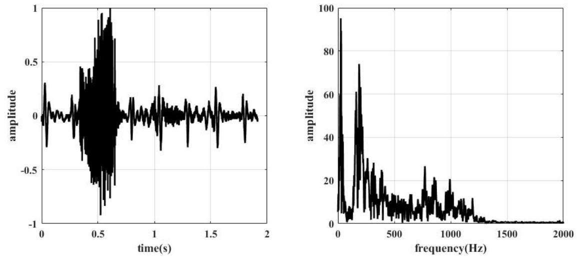

Fig. 3. Stridor and its spectrum

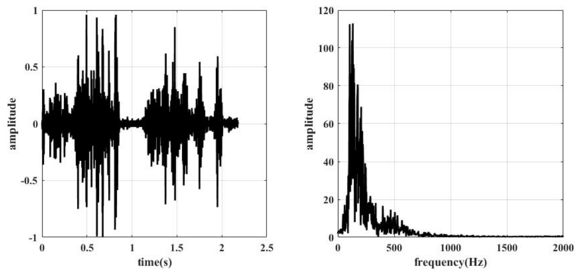

Fig. 4. Pleural rub and its spectrum

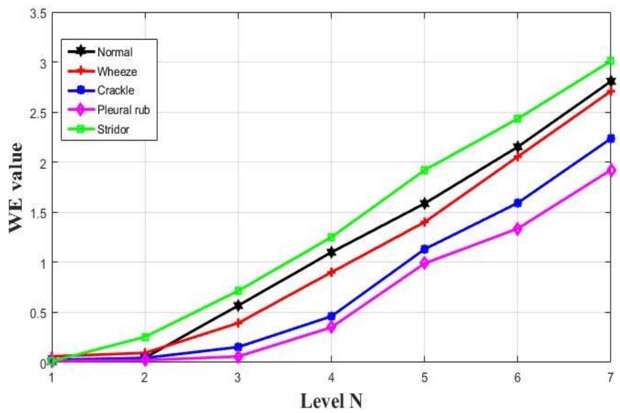

Fig. 5. WPE value for five class data

It also caused the value of WPE_N^j slight for small N and large for large N values. Since Fs = 8000 Hz, the highest frequency of the signal was 4000 Hz. At WPD level 1 there would only be two sub-bands, A1 and D1. Energy sub-band A1 would be far greater than the energy sub-band D1 because the information from lung sound was mostly located in the frequency < 1000 Hz. This caused the value of WPE_N^1 subtle. If the level of decomposition N increased, more sub-bands were formed with energy more evenly distributed so that WPE_N^j would enlarge.

Figure 6 shows the accuracy of WPE using one decomposition level and some mother wavelets. The highest accuracy of 70.71% was generated by Bior2.8 for N = 1. The value of WPE was very small with an average value of 0.0239. As the WPE value was relatively different for each class of data, the accuracy was higher compared to WPE with N > 1.

With the highest accuracy of 70.71% it can be stated that a single WPE value could not produce the good accuracy for pulmonary sound classification. Thus, in this paper, $MWPE_N$ was used for feature extraction.

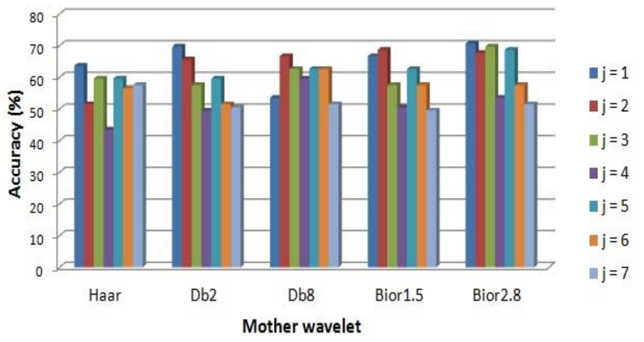

Fig. 6. Accuracy using one decomposition level of WPE

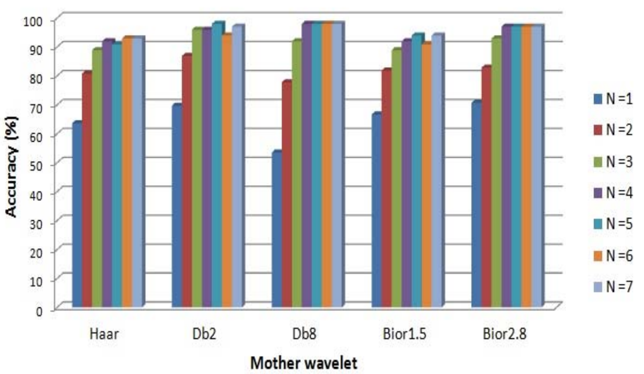

Fig. 7. Accuracy using various N level of $MWPE_N$

Figure 7 presents a displays classification accuracy using $MWPE_N$ with N = 1, …, 7. Db8 in which N = 4 – N =7 produced the highest accuracy of 97.98 %. $MWPE_4$ considered as the best result due to the fewest number of features. The $MWPE_N$ result was better than WPE as shown in Figure 5. The accuracy of $MWPE_N$ using Db8 and Bior2.8 tended to be stable at N = 4 to N = 7 with the accuracy of 97.98% and 96.97% respectively.

On Db2, the accuracy reached the highest result for N = 5 and then decreased for N > 5. As explained earlier, the characteristics of WPE signals depend on the level of decomposition N. The greater the level of decomposition N, the greater the WPE value, even though the accuracy was not always greater. Compared to other WPE methods, producing the features as much as 2^N [6], [10], the proposed method produced a fewer number of features – it was only N features.

The simulation results depicted that the number of decomposition level used to produce an accuracy of 97.98% was only at 4th level. This proposed method also has another advantage that is the usage of multilevel WPD accommodating the multiscale properties of biological signals, especially lung sounds [19].

By varying the decomposition levels, the signal characteristics at each signal resolution can be inferred. The proposed MWPE method is very flexible to be used in other biological signals, for having two parameters to be measured: multiresolution properties of the signal and signal complexity.

V. Conclusion

In this study, we proposed the multilevel wavelet packet entropy (MWPE) for the feature extraction on lung sound classification. Different from the wavelet entropy (WE) calculated from sub-band on DWT, wavelet packet entropy is an entropy calculation using sub-band on WPD. From the test results, it can be concluded that the use of MWPE can yield better accuracy than WPE. The number of features used in MWPE is more than WPE due to MWPE used WPE in certain ranges of decomposition level. It is expected that the proposed method can be utilized in other biological signals such as ECG, EEG, EMG, and others.

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