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An Improved Lung Sound De-noising Method by Wavelet Packet Transform with Pso-Based Threshold Selection

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ABSTRACT

Lung abnormalities and respiratory diseases increase with the development of urban life. Lung sound analysis provides vital information of the present condition of the pulmonary. But lung sounds are easily interfered by noises in the transmission and record process, then it cannot be used for diagnosis of diseases. So the noised sound should be processed to reduce noises and to enhance the quality of signals received. On the basis of analyzing wavelet packet transform theory and the characteristics of traditional wavelet threshold de-noising method, we proposed a modified threshold selection method based on Particle Swarm Optimization (PSO) and support vector machine (SVM) to improve the quality of the signal, which has been polluted by noises. Experimental results show that the recognition accuracy of de-noised lung sounds by the improved de-noising method is 90.03%, which is much higher than by the other traditional de-noising methods. Meanwhile, the lung sound processed by the proposed method sounds better than by other methods. All results make it clear the modified threshold selection can obtain a better threshold vector and improve the quality of lung sounds.

KEYWORDS

Lung sound signal processing; wavelet packet threshold de-noising; threshold selection; particle Swarm Optimization; SVM

1. Introduction

Lung sound is a general term for the sound generated in respiratory system, and contains rich information of pathology and physiology, such as rales or wheeze. The patients that suffer from bronchitis, pneumonia, pulmonary edema may have moist rale on auscultation, and the patients that suffer from bronchial asthma may have wheeze on auscultation. It plays an important role in early diagnosis and prevention of respiratory system diseases (Fard, Moradi, & Saber, 2014; Jingping, Jingzhi, & Yan jun, 1998; Murphy, Vyshedskiy, & Power-Charnitsky, 2004). Due to the impact of movement of body tissues and hardware, lung sound is easily polluted by noise. These noises are relative stable, but deteriorate the features and influence physician diagnosis (Xin, DengYu, & Ye, 2014). Hence the noise from respiratory signal recorded should be removed or suppressed (Cheng & Li, 2010; Lin, Ser, & Zhang, 2011).

In traditional de-noising method, Fourier transform is used to separate the lung sound into high and low frequency components, and the noises are removed by removing the high-frequency part (Moedomo, Mardiyanto, & Ahmad, 2012; Yadollahi & Moussavi, 2009). Because the high frequency part contains some useful information and useful signal and noises are both eliminated at the same time with this method, the signal is distorted. Wavelet transform is a time-frequency localization analysis method. The size of its window is fixed and its shape can be changed. It overcomes the weakness of Fourier transforms that the instantaneous changes in the time domain cannot be reflected in the frequency domain. Wavelet transform is adaptive to lung sound. It applies further decomposition to the low frequency part of lung sound, while wavelet packet transform applies decomposition to both the low frequency and high frequency parts of lung sounds. So we can get much information about lung sounds both in high frequency and low frequency domain and well process the lung sounds, which has a wide spectrum (20~1000 Hz) (Binyong, Haiquan, & Xuechao, 1997; Yi, CaiMing, & YuHua, 2006). The traditional wavelet de-noising method includes global threshold de-noising method, soft/hard threshold de-noising method, wavelet packet decomposition & reconstruction method and adaptive wavelet de-noising method (Bahoura, Hubin, & Ketata, 1998; Huimin, Ruimei, & Yanli, 2012; Misiti, Misiti, & Oppenheim, 1996). The selection of the threshold has a great impact on the effect of de-noising. Currently there are four traditional threshold selection rules including "rigrsure", "sqtwolog", "heursure", "minimaxi" (Misiti et al., 1996). Most of the time, the best threshold cannot be directly got from these rules to achieve the best de-noising effect. So we try to seek out the optimal threshold of wavelet packet de-noising through particle swarm algorithm so as a good recognition rate can be achieved.

In this paper, a modified threshold selection method based on the wavelet packet transform is proposed to obtain a best threshold vector to improve the effect of de-noising.

The paper is organized as follows: The description of the data and pre-processing is provided in Section 2. Section 3 provides the introduction of related algorithm. Section 4 shows the experimental results, and the discussion as well as possible future work is lastly reported in Section 5.

2. Materials and Methods

2.1. Data Acquisition

Lung sounds were recorded from 200 healthy people (20–70 years old) and 100 patients suffering from respiratory

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Figure 1. Lung Sound Acquisition Device Made by Our Team.

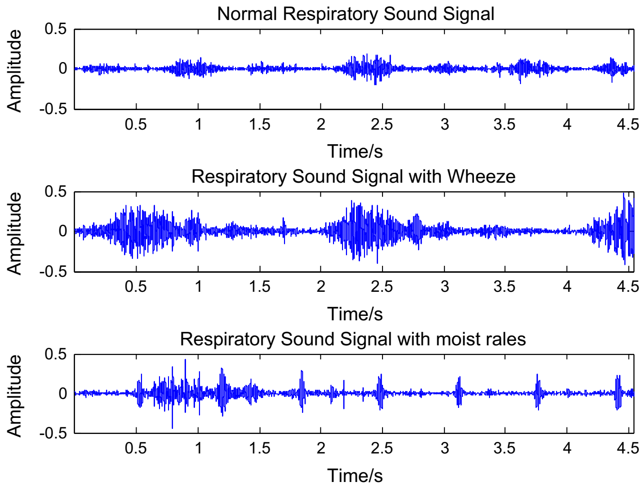

Figure 2. Waveform of Normal and Abnormal Lung Sound.

Table 1. Parameters of Lung Sound Samples.

Sampling frequency/Hz	Sampling period/s	Sampling accuracy/bit
8789	30	16

diseases at the Department of Respiration in the Third Affiliated Hospital of Third Military Medical University, ChongQing, China. All data were acquired by the lung sound acquisition device made by our team as is showed in the Figure 1. The subjects had the age range from new born baby to elderly, and had a wide range of pulmonary diseases including; bronchitis, pneumonia, pulmonary edema and bronchial asthma. These samples have the same sampling frequency 8,789, sampling time 30s and sampling accuracy 16-bits (shown in Table 1). Manual classification results for these lung sounds were obtained respectively from two experienced doctors in the Third Affiliated Hospital of Third Military Medical University by rigorous pulmonary examination.

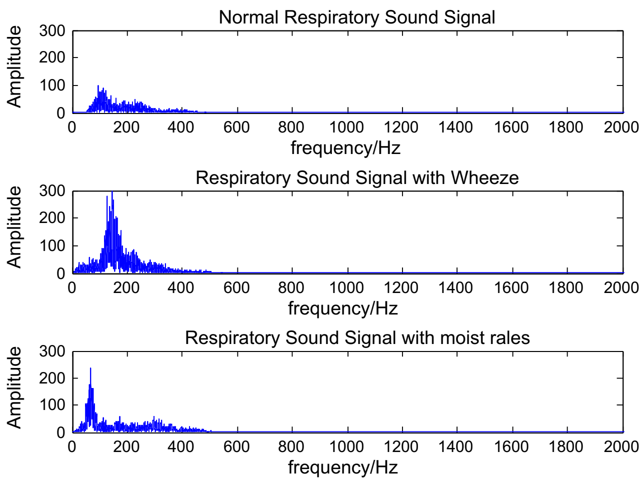

Figure 3. Frequency Spectrum of Normal and Abnormal Lung Sound.

2.2. Pre-processing

Before extracting features, we had to remove the abnormal samples with cough or shape friction sounds, which are considered. Totaling, we extracted 76 samples from healthy subject lung sounds and 55 samples from non-healthy subject lung sounds, all the 131 samples selected are normalized.

2.3. Wavelet Packet Transform

However, Figures 2–3 show time and frequency domain of the normal lung sound and the lung sound with moist rale or wheeze. They contain different energy in different frequency ranges. WT does not further decompose the high frequency bands where the useful information of some lung sound always exists. The outstanding excellence of WPT over WT is that it provides a better frequency resolution in the high frequency domain. For lung sounds, the useful frequency range is from 20–2000 Hz, therefore WPT can provide better high frequency information required. A signal can be decomposed into a set of wavelet packet nodes with the form of a full binary tree by WPT (Misiti et al., 1996).

Let $U_{0,0}$ be a vector of R_0, representing the node 0 of the wavelet tree. Then at each level the vector space is decomposed into two orthogonal subspaces given according to the following Equation:

$$U_{j,k} = U_{j+1,2k} \oplus U_{j+1,2k+1} \tag{1}$$

where j represents the number of layer, and k $(k = 0, \ldots, 2^j - 1)$ indicates the node vector in level j. The decomposition is continued until the maximum decomposition level J. The theory of WPT is shown in Figure 4. First, the WPT function $W^n_{j,k}(t)$ is shown below:

$$W^n_{j,k}(t) = 2^{j/2} W^n(2^j t - k) \tag{2}$$

where the variable j and k are the scale and translation parameters respectively; $n = 0, 1...$ is the oscillation parameter. The first two wavelet packet functions with $j = k = 0$ are the scaling function $\Phi(t)$ and mother wavelet function $\psi(t)$ as below:

$$W^0_{0,0}(t) = \Phi(t) \tag{3}$$

$$W^1_{0,0}(t) = \Psi(t) \tag{4}$$

The WPT functions for $n = 2, 3, ...$ are defined below:

$$W^{2n}(t) = \sqrt{2} \sum_k h(k) W^n_{1,k}(2t - k) \tag{5}$$

$$W^{2n+1}(t) = \sqrt{2} \sum_k g(k) W^n_{1,k}(2t - k) \tag{6}$$

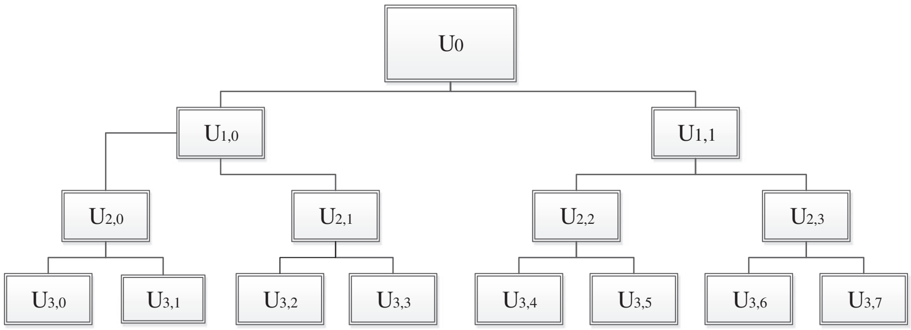

Figure 4. Diagram of Three-layer Wavelet Packet Decomposition.

where $h(k) = 1/\sqrt{2}\langle\varphi(t), \varphi(2t-k)\rangle$ and $g(k) = 1/\sqrt{2}\langle\psi(t), \psi(2t-k)\rangle$ are the wavelet coefficients of low pass and high pass filters respectively. The value of $S^n_{j,k}$ represent the correlation between signal $x(t)$ and the wavelet packet functions $W^n_{j,k}$ is shown as Equation (7):

$$S^n_{j,k} = \langle x, W^n_{j,k}\rangle = \int_{-\infty}^{\infty} x(t)W^n_{j,k}(t)\mathrm{d}t \qquad (7)$$

Signal $x(t)$ is decomposed into 2^j wavelet frequency bands with the level j. In the wavelet packet tree, the nodes are ranked by (j, n). The tree nodes of the WPT consist of equal band width for the scale parameter j. After reconstructing the coefficients layer by layer, we obtain the reconstructed signal as shown in Figure 4.

Because the lung sounds have a wide frequency range, some important information must be left out after reconstruction of part of the wavelet coefficients. Meanwhile, the lung sounds in each frequency band may be polluted by noises. By wavelet coefficient election, only the noises whose frequency is not in the selected frequency domain are removed from the original signal, but those inside the selected frequency domain cannot be eliminated effectively. In this case, the improved threshold de-noising method is used to remove the noises inside the selected frequency domain.

2.4. Threshold De-noising

The nature of multi-scale analysis method is to decompose lung sounds into different signals in different frequency range (Huimin et al., 2012). The information in different scales can represent characteristics of lung sound in different frequencies (Bahoura et al., 1998). By Wavelet packet transform, the lung sound is decomposed into 2^j frequency bands at the level j. The diagram of three layers wavelet decomposition is shown in Figure 4, where $U_{1,i}, U_{2,i}, U_{3,i}$ are corresponding to the sound's approximate and detailed parts in different layers, respectively. The noises existing in useful lung sound are usually contained in all the coefficients. The wavelet packet coefficients in all the frequency bands are processed by threshold de-noising method to reduce noises and the de-noised signal is reconstructed by these processed wavelet coefficients through wavelet packet reconstruction (Fuwei & Shan-chuan, 2006; Gao-zhong & Yan-hong, 2007; Hua, Chuan-sheng, & Xiao-mei, 2007; Lai & Tseng, 2004; Liao, Chen, & Chung, 2001).

2.5. Overview of PSO

PSO is one of the most widely used techniques for parameter optimization. PSO can obtain the global best solution efficiently and has less chance to run into partial optimization than other algorithms. In PSO, a number of units are initialized to construct a colony moving around in an N-dimensional space looking for the best solution. Each unit updates its coordinates in the N-dimensional space and use the best coordinates that has achieved so far by that unit (pbest) and another best value obtained so far by all units (gbest) (Jun & Ruifeng, 2009; Sathya & Kayalvizhi, 2010).

Each particle tries to modify its position using the following information:

(1) Current positions;
(2) Current velocities;
(3) Distance between the current position and pbest;
(4) Distance between the current position and gbest.

In this paper, PSO is used to search for the best threshold vector and parameters of SVM, and the recognition rate of SVM serves as the fitness of PSO.

2.6. SVM Optimized by PSO

In this section, The SVM optimized by PSO (PSO-SVM) algorithm is used as the final classification algorithm. The following is the detailed introduction of algorithms.

2.6.1. Outline of SVM Classification

Support Vector Machine (SVM) is a supervised learning model, usually used for classification, pattern recognition and regression analysis (Subasi, 2013). The SVM algorithm has the quality of the use of the kernel-induced features paces and good generalization ability (Shen, Shi, Kong, & Ye, 2007). SVM algorithm has the quality of the use of the kernel-induced features paces and good generalization ability. SVM separates data that cannot be separated linearly, by mapping the sample space to a high-dimensional space. Generally, it is an optimization problem to select a proper kernel function to achieve linear separation through nonlinear transformations (Abe, 2005; Burbidge, Trotter, Buxton, & Holden, 1998; Burges, 1998).

For optimal performance of SVM, different kernel functions such as radial basis kernel function (RBF), polynomial and sigmoid are used to make comparison (Liao, Fang, & Nuttle, 2004; Lin & Lin, 2003). RBF proves to perform well than other kernel function for these features.

2.6.2. PSO-SVM Classification Method

In this section, the RBF kernel function is used for the SVM classifier and the parameters (C and g) are optimized using PSO system. Classification accuracy is criteria to design the fitness function. The PSO-SVM algorithm is applied for the lung

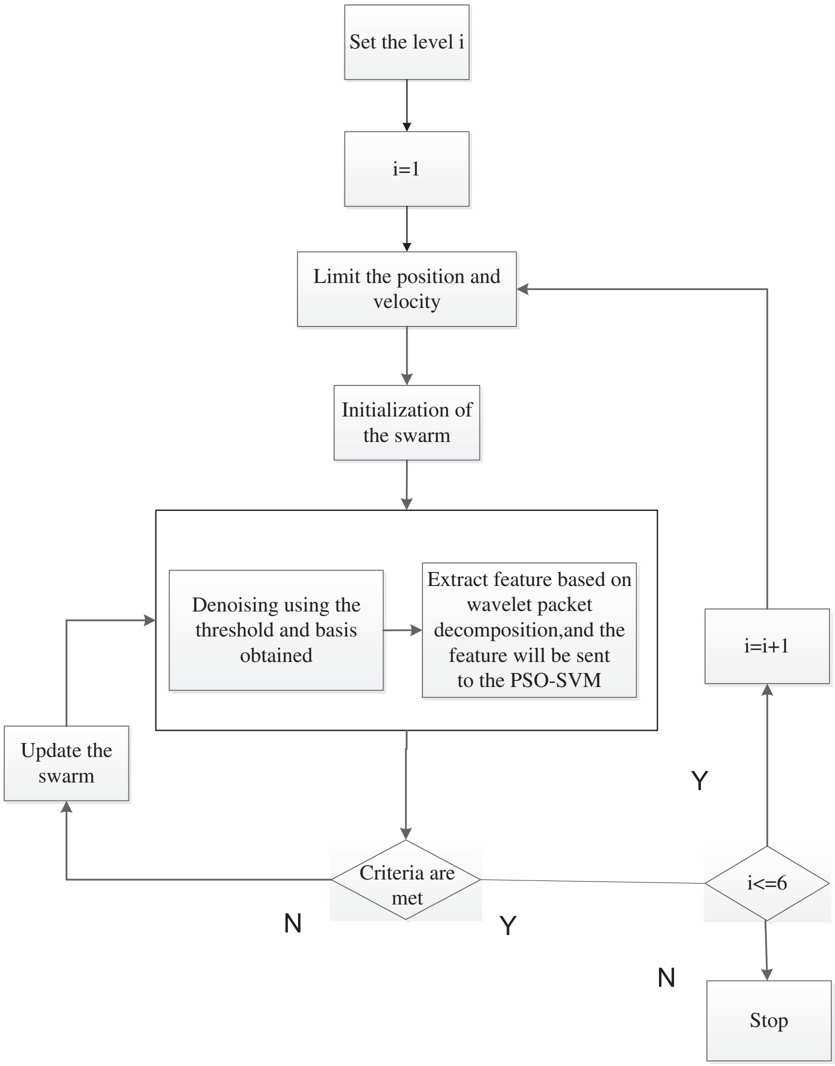

Figure 5. Flowchart of the Proposed Algorithm.

Table 2. Frequency Range of Corresponding Wavelet Coefficients.

Level	Si,0 (Hz)	Si,1 (Hz)	Si,2 (Hz)	Si,3 (Hz)	Si,4 (Hz)	Si,5 (Hz)	Si,6 (Hz)	Si,7 (Hz)
1	0~2,196	2,198~4,394						
2	………	………	………	………				
3	………	………	………	………				
4	………	………	………	………				
5	0~136	137~274	413~549	275~412	**550~686**	**687~823**	**824~960**	**961~1,097**
6	**0~68**	**69~136**	**206~274**	**137~205**	**482~549**	**413~481**	**275~343**	**344~412**

sounds classification. The aim of this algorithm is to improve the SVM classifier accuracy by automatically adjusting the SVM parameters. In order to achieve this, the system is derived from an optimization method based on PSO.

2.7. Algorithm Steps

The flowchart of the proposed algorithm can be seen in Figure 5. The algorithm steps are listed as follows:

Step 1 Initialization of the swarm: For a population size *p*, which is determined by the number of decomposition level, wavelet bases and parameters of SVM. The threshold limits is determined by the maximum value of the wavelet coefficients of each samples.

Step 2 De-noising using the threshold and wavelet bases obtained. Extract feature based on wavelet packet decomposition, because lung sounds mainly range in 20~1000 Hz, We extract the energy of six wavelet coefficients at the sixth layer and the energy of four wavelet coefficients at the fifth layer (the highlighted parts in bold in Table 2) (Kahya, Yeginer, & Bilgic, 2006; Liu & Zhang, 2006; Peng, 1999) these features will be sent to the PSO-SVM (Palaniappan & Sundaraj, 2013).

Step 3 Evaluation of the objective function. The objective function values of the particles are evaluated using the MSE.

MSE is defined as:

$$\mathrm{MSE} = \left(\left(\sum_i \mathbf{S}'(i) - \mathbf{S}(i)\right)^2\right)^{1/2} \tag{8}$$

where $\mathbf{S}$ is the vector of target value, $\mathbf{S}'$ is the vector of output value.

Step 4 Initialization of pbest and gbest: The particles of the swarm are initialed as pbest values of the particles. The best value among all the pbest values is set as gbest.

Step 5 Evaluation of velocity: The new velocity for each particle is computed using Equation (9).

X and V denote the particle's position and its corresponding velocity in search space respectively. W is the inertia weight, C_1 is the cognitive parameter, which pulls each particle towards local best position; C_2 is the social parameter, which pulls the particle towards global best position.

$$\begin{aligned} V_{i,n}^{k+1} = W \times V_{i,n}^{k} + C_1 \times rand_1 \times (\mathrm{pbest}_{i,n} - X_{i,n}^{k}) \\ + C_2 \times rand_2 \times (\mathrm{gbest} - X_{i,n}^{k}) \end{aligned} \tag{9}$$

Step 6 Update of swarm: The particle position is updated using Equation (10). If the new particle performs better than the previous pbest, the new particle is set to pbest. Similarly, gbest value is determined among all the new pbest.

$$X_{i,n}^{k+1} = \begin{cases} X_{i,n}^{k} + V_{i,n}^{k+1} & \text{if } \; X_{\min\ i,n} \le X_i^{k+1} \le X_{\max\ i,n} \\ X_{\min\ i,n} & \text{if } \; X_i^{k+1} \le X_{\min\ i,n} \\ X_{\max\ i,n} & \text{if } \; X_i^{k+1} \ge X_{\max\ i,n} \end{cases} \tag{10}$$

Step 7 Stop: When stopping the criteria is met, the value of gbest is the optimal threshold values. Otherwise, the procedure is repeated from step 5.

3. Results and Discussion

In order to analyze and compare the six de-noising methods, Matlab R2011 is selected as the simulation software. A set of experimental studies was discussed on 131 lung sounds. The results were then contrasted with the recognition rate to verify the optimality of the features selected. The results of different algorithms were also discussed. We separated the data into a training group and an experimental group and performed a 5-fold cross validation. Because there are no original lung sounds as references, we use recognition rate to measure de-noising effects.

Table 3. Samples Used in this Paper.

Type	Lung sound	Wheezing	Moist rale	Total
Training	76	40	15	131
Testing	76	40	15	131

Table 4. MSE and Recognition Rate in Different Layer by PSO Optimized Threshold.

Decomposition level (Frequency band)	Best bases	Recognition rate(true/total)
First (2197 Hz)	sym2	90.03%
Second (1,098 Hz)	db4	90.03%
Third (549 Hz)	db7	90.03%
Fourth (274 Hz)	db6	90.03%
Fifth (137 Hz)	db6	90.03%
Sixth (68 Hz)	db2	90.03%

Table 5. Recognition Rate with Different De-noising Method.

De-noising method	Recognition rate
Without de-noising	54.9%
De-noising method proposed	90.3%
Multi-threshold	62.6%
Soft threshold	74.8%
Hard threshold	72.5%
Wavelet packet decomposition and reconstruction	74.8%
Adaptive wavelet threshold	76.3%

Db N wavelet and Sym N wavelet are used here, and the data are separated into the training group and testing group (showed in Table 3).

After repeatedly using the method proposed to get best threshold from level 1 to level 6, we use the optimal threshold for de-noising to improve the recognition rate as showed in Table 4.

It can be found from Table 4 that the algorithm proposed perform well and the lung sounds de-noised are easy to identify in all of the Decomposition level. The de-noising effect of db N wavelet is better than that of sym N wavelet for lung sounds, db4~db7 perform better than other db N wavelet. From level 3 to level 6, the recognition rate doesn't increase. It is found that less difference in de-noising effect can be found from level 3 to 6. In consideration of calculation amount, we compare the modified threshold de-noising method with other five kinds of wavelet de-noising method in the third layer.

After processing the lung sounds based on the six methods, the features of lung sounds are extracted and sent to the PSO-SVM.

From Table 5, it can be found that the modified threshold de-noising method performs better than other traditional wavelet de-noising methods to improve the recognition rate of lung sounds. From Figures 6–7, it can also be found that the characteristics of lung sounds are difficult to identify. After de-noising, the expiratory phase and the inspiratory phase can be easy to observe. Meanwhile, sounds processed by the proposed method sounds better than by other methods according to doctor judgement.

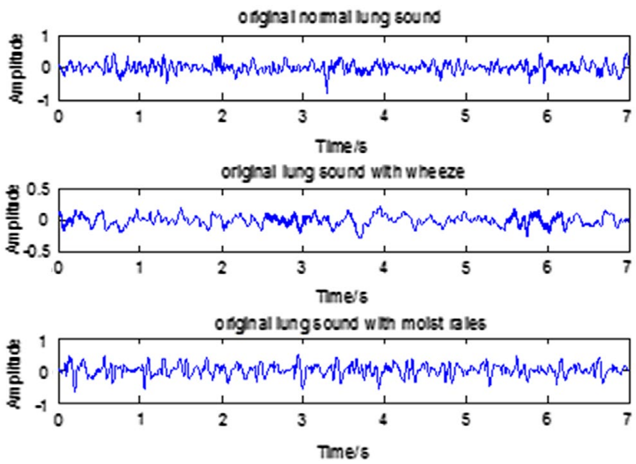

Figure 6. Waveform of Normal and Abnormal Lung Sounds.

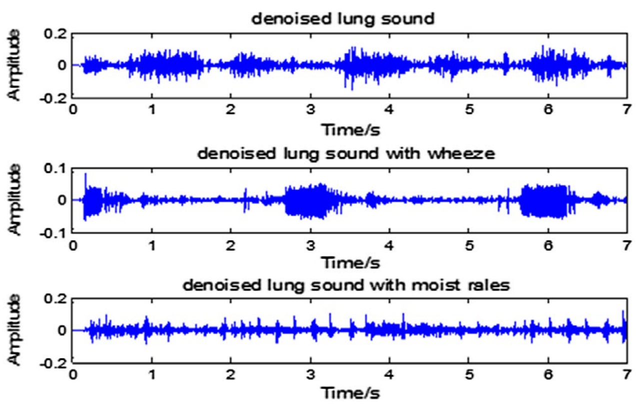

Figure 7. Waveform of Normal and Abnormal Lung Sounds Before De-noising After De-noising.

4. Conclusion

After wavelet packet transform, the lung sound signal only concentrate in some wavelet coefficients, and the noises are usually contained in all the coefficients. The noise in lung sounds is simpler to be removed by set an appropriate threshold vector and the lung sound signal is retained. There is a definite gap between the threshold obtained by traditional threshold selection method and the best threshold. PSO is utilized to search for the best threshold vector. The normal lung sound and the lung sound with moist rale or wheeze contain different energy in different frequency ranges. By using the wavelet packet transform to extract features, the normal lung sound and the lung sound with moist rale or wheeze can be easy to identify with effective de-noising. So the recognition rate of PSO-SVM serves as the fitness of PSO to search for the best threshold vector. The characteristics of five traditional wavelet threshold selection methods are analyzed and a modified wavelet packet threshold selection method is proposed. The experimental results show that the modified threshold method overcomes the shortcomings of threshold being discontinuous in all the wavelet coefficients. It is superior to the traditional threshold selection method for improving SNR and recognition rate.

Future studies will systematically investigate characteristics of different types of noise in lung sounds, for a variety of activities under different scenarios.

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