Empirical Mode Decomposition and Wavelet Decomposition in Respiratory Sounds Processing

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Article

Empirical Mode Decomposition and Wavelet Decomposition in Respiratory Sounds Processing

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Abstract: In order to process respiratory sounds to achieve acquiring available information of sound signals Empirical Mode Decomposition (EMD) and Wavelet Decomposition (WD) are applied separately to analyze lung sound signals. The de-noise of original signals is processed with spectral subtraction method. EMD divides the signal into independent Intrinsic Mode Functions (IMFs). Moreover, WD method decomposes the signal with wavelet transform. After receiving the decomposition signals of EMD and WD, a comparation is demonstrated. According to the results, WD has 85% signal information concentrate on layer 7 and Hilbert diagram shows the EMD owns more efficiency in decomposing signals with information keeping.

Key words: Empirical Mode Decomposition; Wavelet Decomposition; Spectrum Subtraction; Hilbert Transform.

1. Introduction

Recently, COVID-19 becomes a serious worldwide issue which is need to be fixed. This virus leads to serious lung disease which is the reason many people passed in the past year. In the procession of curing the lung disease to obtain the breathing information is extremely significant. The respiratory sounds can demonstrate important lung information of patients.[1] Thus, analyzing of respiratory sounds of patients to achieve getting the information is significant.[2]-[3] This article is going to discuss about the decomposition methods of original respiratory sound signals efficiency. The methods include Empirical Mode Decomposition (EMD) and Wavelet decomposition.

After the acquisition of the respiratory sounds, the first step is to pre-process the signal. Respiratory sounds are sounds of breathing within the lungs over the chest wall. [4] During the period of breathing and acquisition of signal, the noise cannot be avoided. Moreover, the lung is near to the heart. Thus, the heart sound is unpreventable noise, which can have severe influence on acquisition of lung sound signals. [5]

There are many methods to de-noise the signals. Hadjileontiadis et al. demonstrated a method that using the combination of fractal dimension (FD) and EMD eliminate the noise of lung sound signals. [6] Emmanouilidou et al. [7] introduced adaptive subtraction method to decrease the heart sound noise of respiratory signal. Moreover, in 2021, Haider used Spectral Subtraction method with EMD and hurst to do the de-noise of lung sound signals, which is proved has excellent performance.[8] In this article, the method of Spectral Subtraction De-noise method is chosen to do the noise elimination.

Empirical mode decomposition was introduced in 1998 by N.E. Huang to process non-linear and unstable signals.[9] After EMD method coming out, a bunch of optimization algorithms and papers appeared based on the research result of N.E. Huang. [10] EMD algorithm has widely application category in medical area, and it can be used for analyzing lung sounds. [11]

According to the characteristics of Wavelet Transform (WT), mature and low-complexity, it has been widely used for processing respiratory sound signals. Hossain I et al proposed a method using WT combine with spectral characteristics to build filter of respiratory sounds signals. [12] In 2004, a method based on fast WT was used for lung sounds classification.[13] In this article, based on EMD and WD respiratory sound signals will be analyzed. The signal will be de-noise by spectrum subtraction method, then using EMD and WD to analyze the denoise signals separately. In the end, the efficiency of keeping the original signals characteristics will be compared.

For respiratory sound signals analyzing, signal information keeping is a significant problem. This paper is trying to compare EMD and WD to examine the ability of keeping original signal information. Firstly, this article chooses spectral subtraction de-noise method in pre-processing original signal. Secondly, the EMD method is demonstrated. Moreover, WD is used for signal decomposition and Shannon entropy of relative wavelet energy is used for texting.

2. Spectral Subtraction De-noise

In this paper, the de-noise method based on spectral subtraction was used to do the voice signal de-noise. First of all, assuming the voice sequence as $x(n)$ to do the window framing of $x(n)$. Thus, $x_i(m)$ can be got after window framing. Afterall, Discrete Fourier Transform method is used to deal with $x_i(m)$. The equation below can be achieved:

$$x_i(k) = \sum_{m=0}^{N-1} x_i(m) e^{\left(j\frac{2\pi mk}{N}\right)} \qquad k = 0,1,2,\dots,N-1 \tag{1}$$

Phase angle is obtained with equation (2)

$$X_{angle}^{i}(k) = \arctan\left[\frac{Im\left(x_i(k)\right)}{Re\left(x_i(k)\right)}\right] \tag{2}$$

Then the energy of the noise is:

$$D(k) = \frac{1}{NIS}\sum_{i=1}^{NIS} |X_i(k)|^2 \tag{3}$$

After all the steps above, the below equation can be used for de-noise:

$$|x_i(k)|^2 = \begin{cases} |X_i(k)|^2 - a \times D(k) & |X_i(k)|^2 \geq a \times D(k) \\ b \times D(k) & |X_i(k)|^2 < a \times D(k) \end{cases} \tag{4}$$

The spectral subtraction de-noise algorithm block diagram is showing in figure 1.

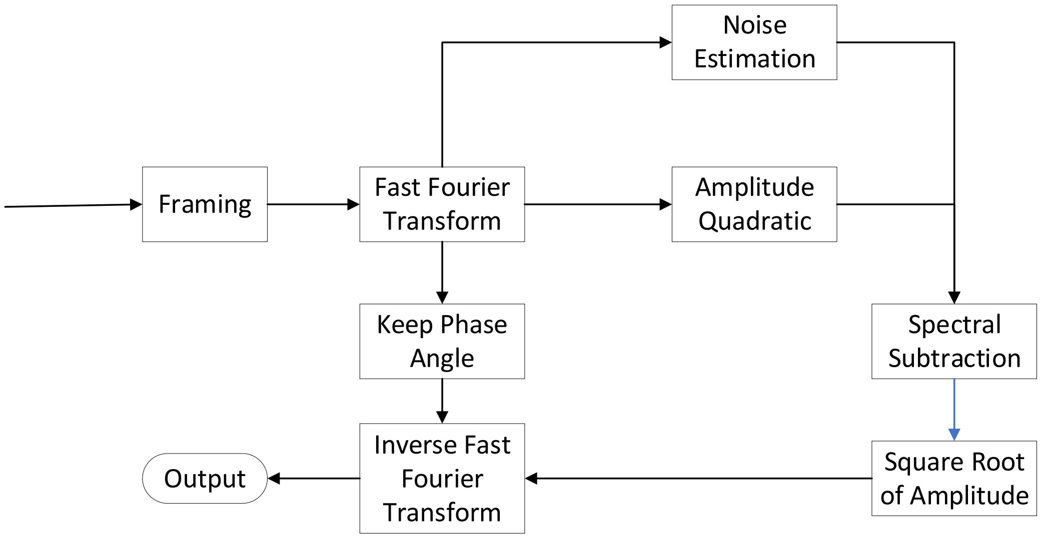

Figure 1. spectral subtraction de-noise block diagram

The de-noise result of the original signal is showing in Figure 2. As can be seen in the figure, with this de-noise method, the noise can be decreased efficiently, and the characteristics of the signals can be kept.

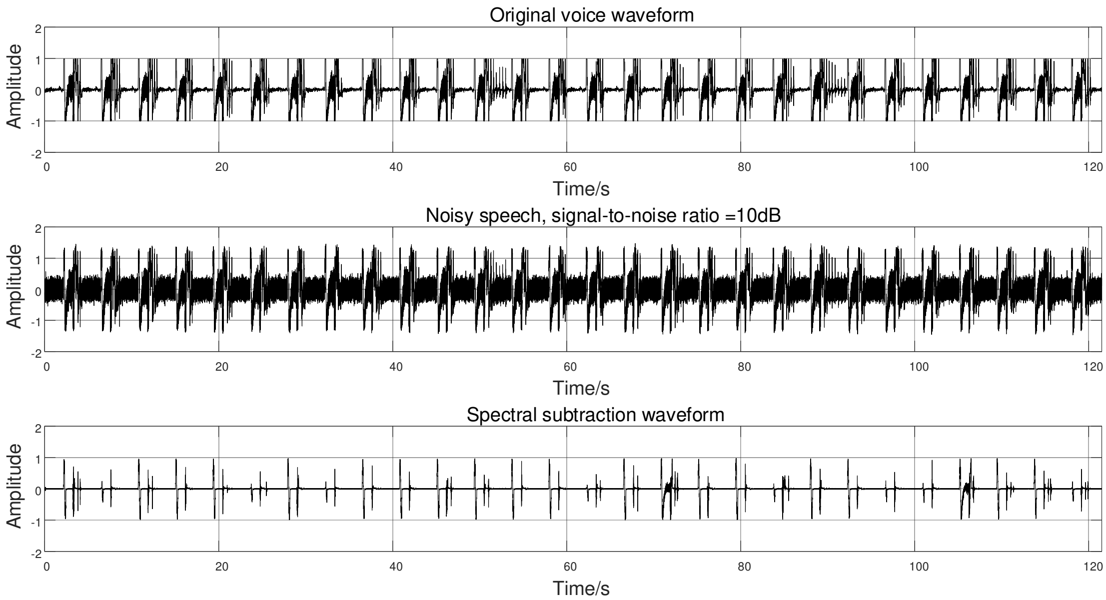

Figure 2. Spectral subtraction waveform comparation

As can be seen from figure 2, the spectrum can provide efficiently de-noise of the respiratory signal. After the denoise, the characteristics of the original signal are still kept. With the 10 DB signal to noise ratio (SNR), the proposed method can eliminate the noise contaminations very well. The respiratory sounds signals were started sampling at 4000 Hz rate. Afterall, let the result pass a Butterworth Band-pass filter of 20-2000Hz, which can eliminate all the high frequency noises. Moreover, the spectral subtraction was used to get further outcoming of the denoise of signals.

3. Empirical mode decomposition

EMD method has advance in non-stationary and non-linear signals analysis. The respiratory sound signal can be divided into several independent intrinsic mode functions (IMFs) based on frequency difference. [13]

To achieve the EMD analysis, the first step is to get the mean value of upper and lower envelop of input signal $x(t)$. Assuming the mean value as m_1, the equation (5) below can be got:

$$h_1 = x(t) - m_1 \tag{5}$$

The second step is using h_1 as new $x(t)$ to run the process above again until h_1 satisfy the IMF conditions then output the first IMF as C_1.

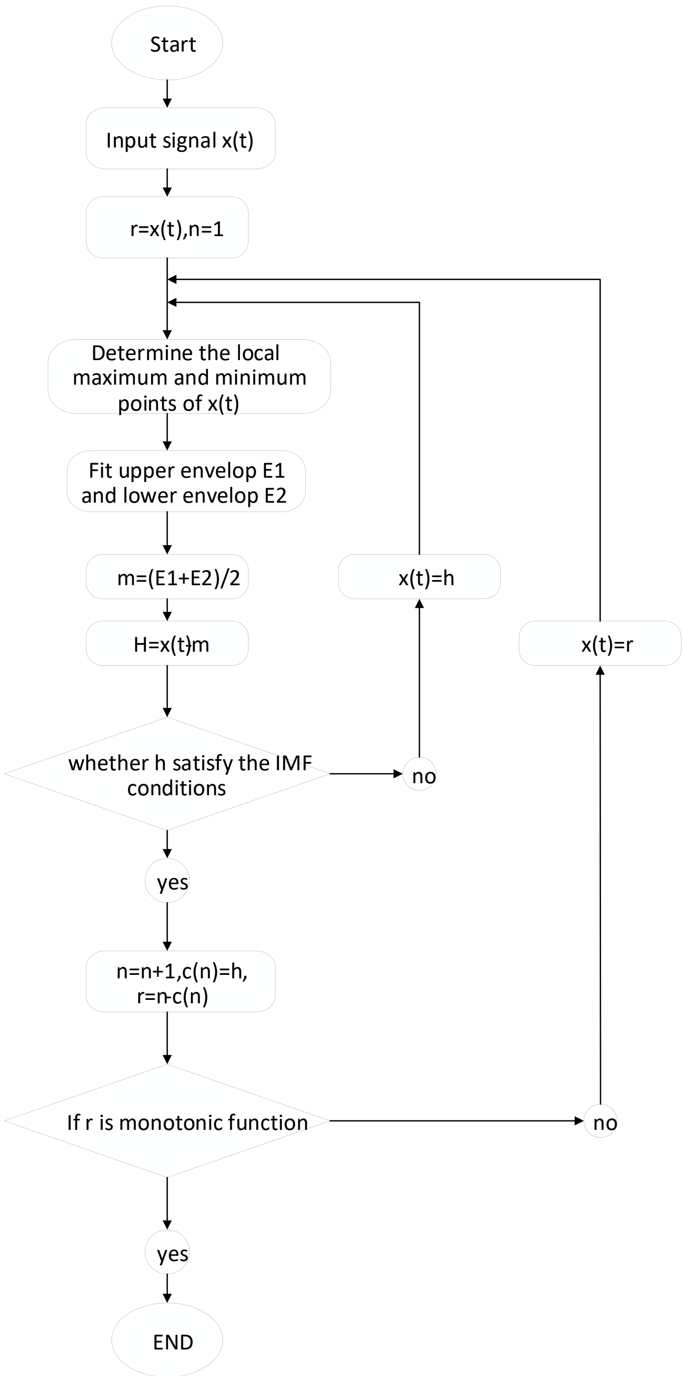

Figure 3. Empirical mode decomposition algorithm flowchart

With the separation of C_1 and $x(t)$, a signal r_1 without high-frequency components is obtained.

$$r_1 = x(t) - C_1 \tag{6}$$

Repeat the steps above until the remain signal is monotonic function.

$$r_n = r_{n-1} - C_n \tag{7}$$

Overall, the original signal $x(t)$ can be represent as below:

$$x(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \tag{8}$$

The whole algorithm flowchart of EMD is demonstrated in Figure 3.

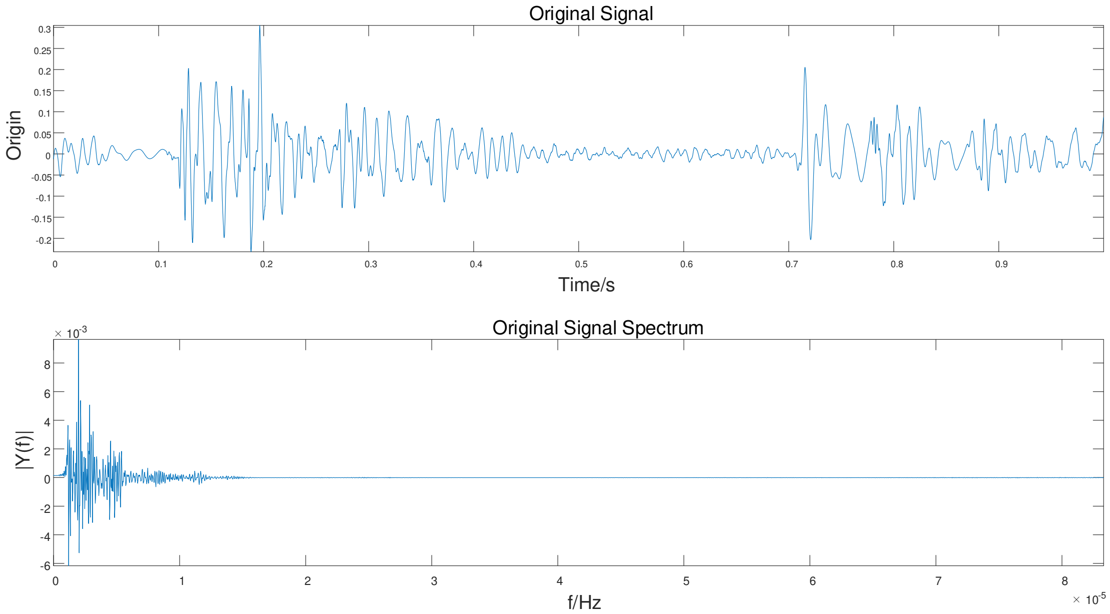

Figure 4. original signal and signal spectrum of mild sputum stasis

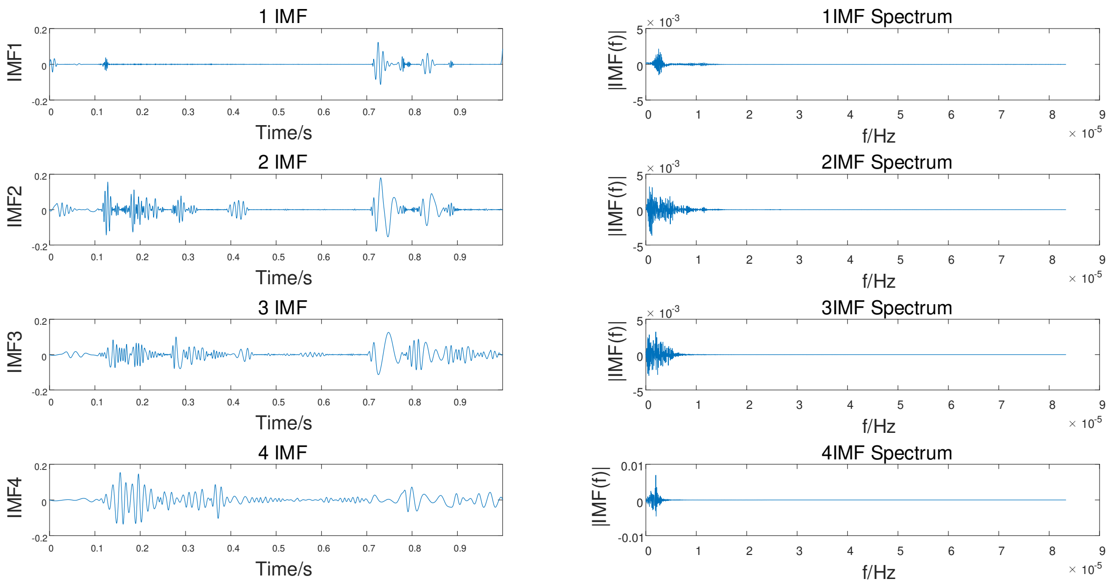

Figure 5. IMF 1 to 4 of mild sputum stasis respiratory sound and spectrum

According to the method described above, the different signals were processed with EMD. Figure 4 shows the original signal of mild sputum stasis respiratory lung sounds. The spectrum of original signal is illustrated in Figure 4 as well.

According to the characteristics of EMD, the 1st to 4th IMFs are the independent components with higher frequency then the rest. In this paper, only the first 4 IMFs results are given. Based on figure 5, IMF 3 and 4 can reflect the characteristics of original signal most effectively. Thus, the IMF 4 was chosen to illustrated the characteristics. Figure 6 is showing the signal of IMF 4 and spectrum. Moreover, the envelop of IMF 4 and instantaneous frequency are also given.

Figure 6 demonstrates that the mild sputum stasis respiratory sound has slight change in instantaneous frequency change.

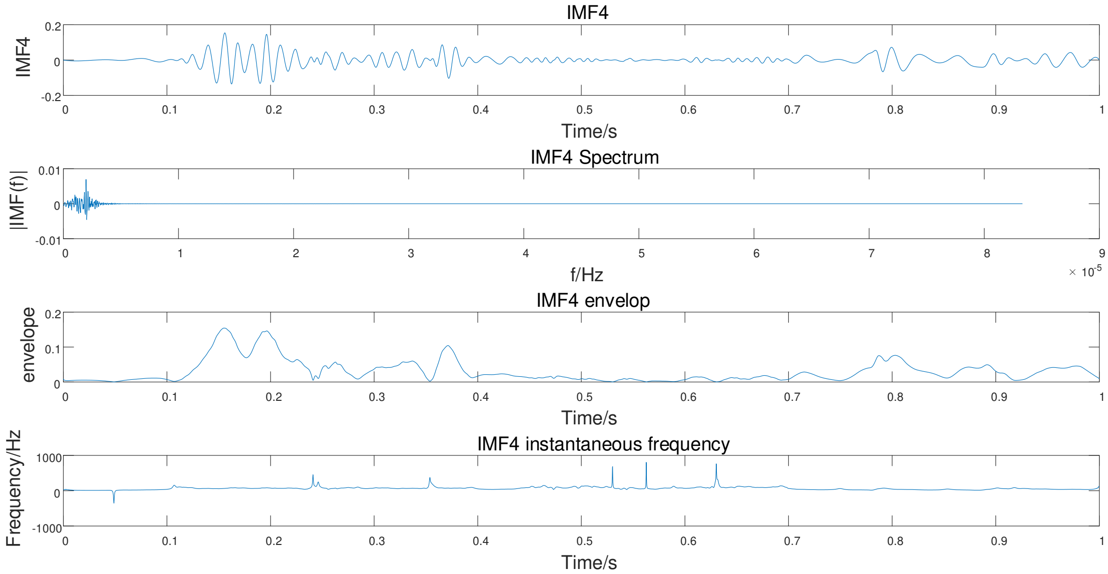

Figure 6. mild sputum stasis respiratory sound IMF 4 characteristics

In figure 7 and 8, the comparation of light severe and severe of sputum stasis can be made. As shown in the figures, the mild sputum stasis signal has regular breath signal with the longest period. The light severe sputum stasis signal shows that the breath become more hush and unregular. The severe sputum stasis original signal demonstrates that the more severe sputum stasis, the more unregular signal it is.

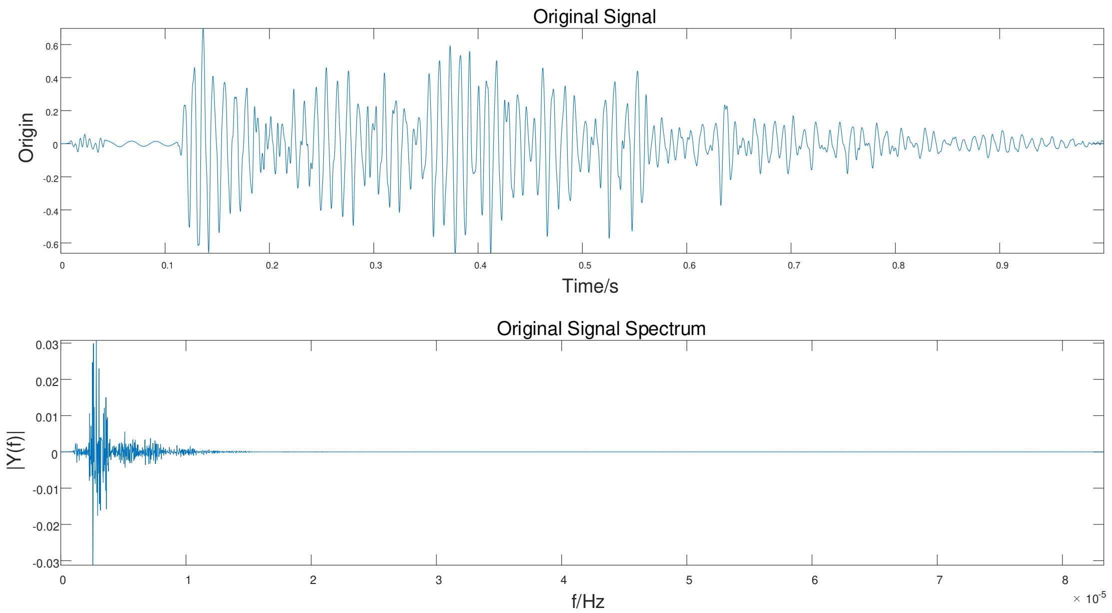

Figure 7. Original signal of light severe sputum stasis

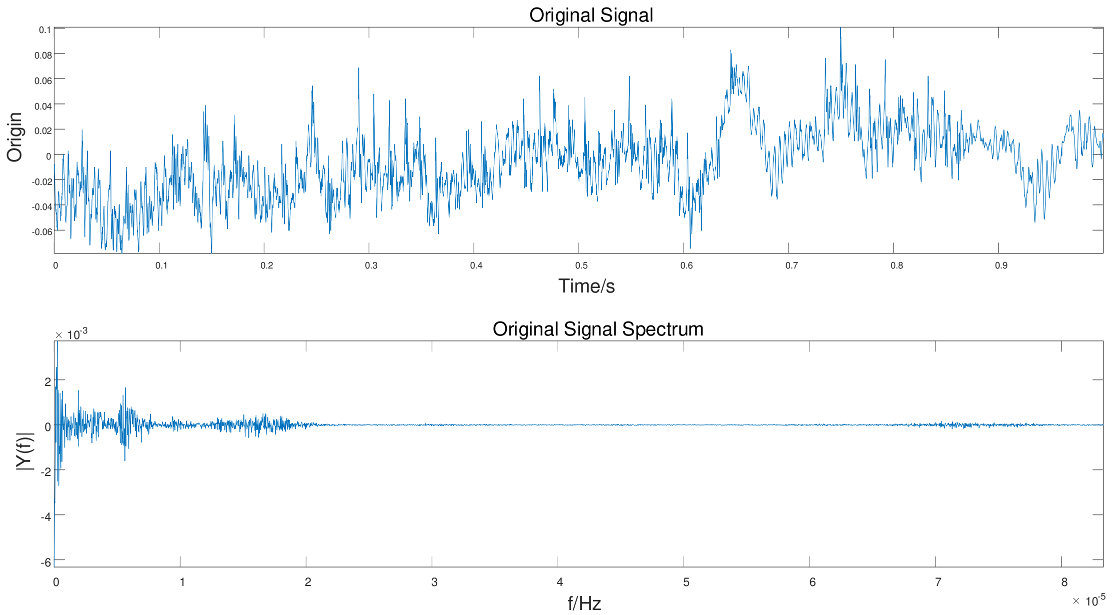

Figure 8. Original signal of severe sputum stasis

Figure 9 and 10 show the 1 to 4 IMFs of light severe sputum stasis and severe sputum stasis signals, which convey the most information of original signals.

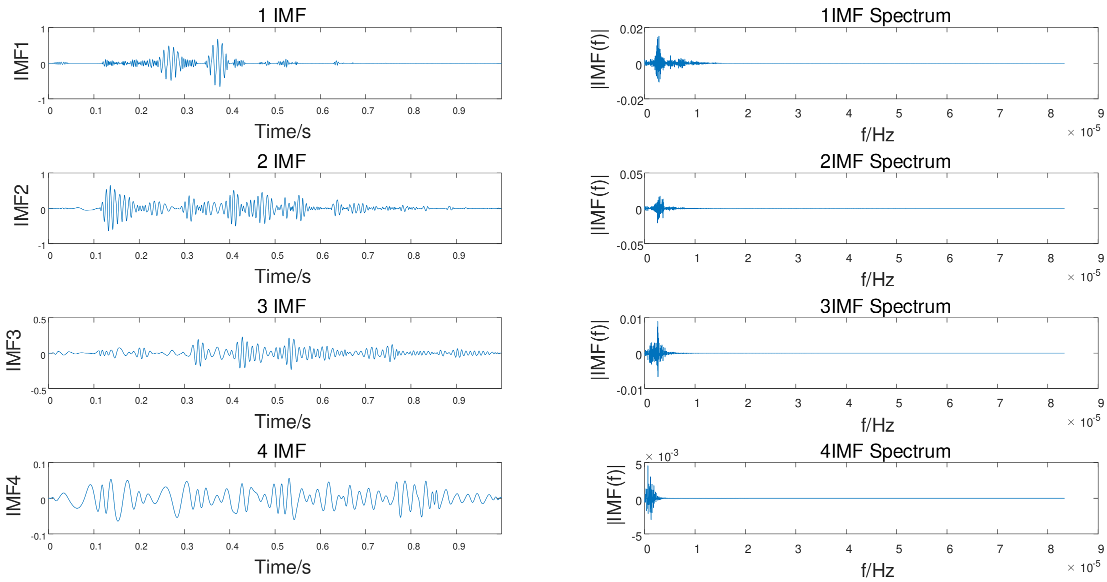

Figure 9. 1 to 4 IMFs light severe sputum stasis

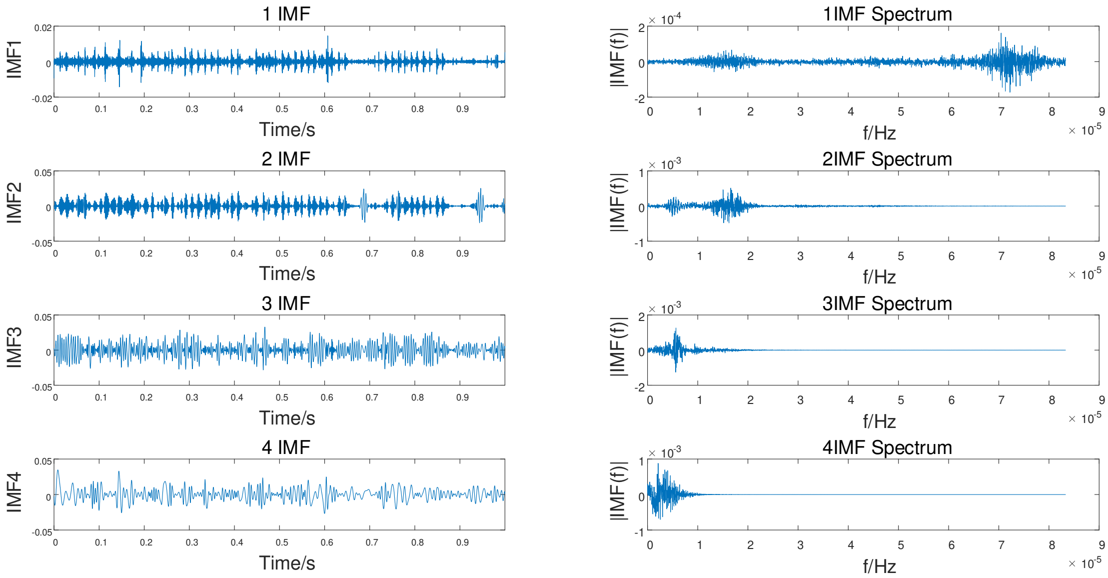

Figure 10. 1 to 4 IMFs of severe sputum stasis

It can be seen from figure 9 and 10 that the combination of the IMFS and spectrum results are almost equal to the original signal. Moreover, according to the comparation between severe sputum stasis IMFs and mild sputum stasis IMFs, the severe sputum stasis causes more unregular and strong sound noise.

The results of the figure 9 and 10 comparing to original signals respectively demonstrate that the IMFs has similar components which is similar to the original signal. In other word, all the IMFs can demonstrate part information of original signal. The combination of all IMFs information equal to original signal, which means the whole information can be almost kept.

After got the IMFs, then do the Hilbert translation for every IMFs:

$$\hat{h}_i(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{\hat{h}_i(\tau)}{t-\tau} d\tau \tag{9}$$

$\hat{h}_i(t)$ is represent each IMFs, then construct analytic function:

$$z_i(t) = h_i(t) + j\hat{h}_i(t) = a_i(t)e^{-j\varphi_i(t)} \tag{10}$$

After that the amplitude function can be got:

$$a_i(t) = \sqrt{{h_i}^2(t) + {\hat{h}_i}^2(t)} \tag{11}$$

The instantaneous frequency $f_i(t)$ is:

$$f_i(t) = \frac{1}{2\pi}\omega_i(t) \tag{12}$$

Then:

$$x(t) = Re\sum_{i=1}^{n} a_i(t)e^{-j\int \omega_i(t)dt} \tag{13}$$

Thus, the Hilbert Diagram can be obtained according to the function (14)

$$H(\omega, t) = Re\sum_{i=1}^{n} a_i(t)e^{-j\int \omega_i(t)dt} \tag{14}$$

The Hilbert Diagram can reflect the amplitudes of IMFs change in the whole frequency band with time and frequency change.

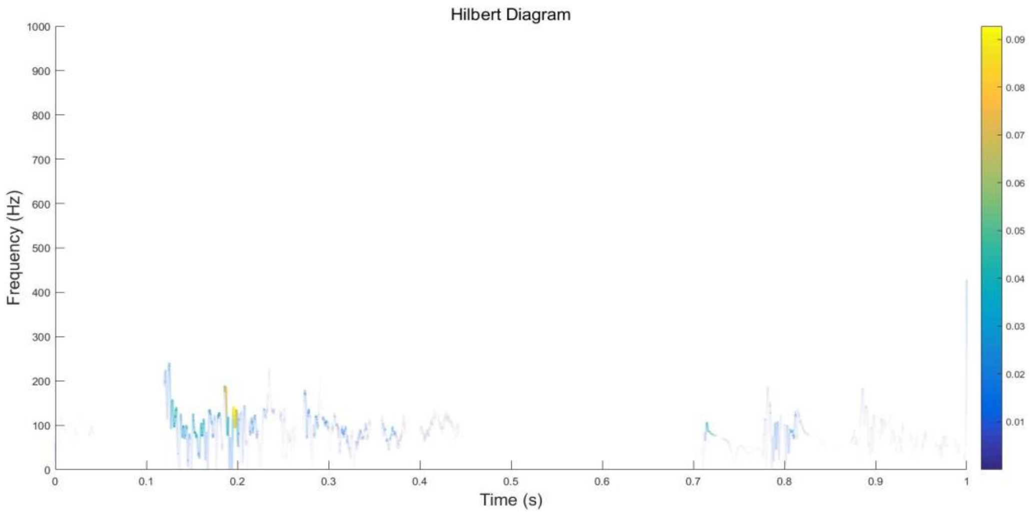

Figure 11. Hilbert Diagram of mild sputum stasis

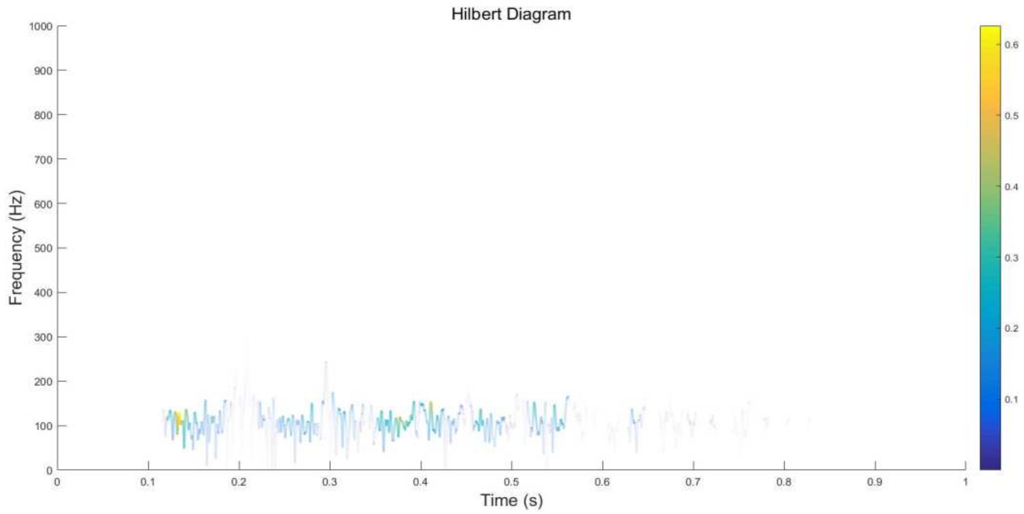

Figure 12. Hilbert Diagram of light severe sputum stasis

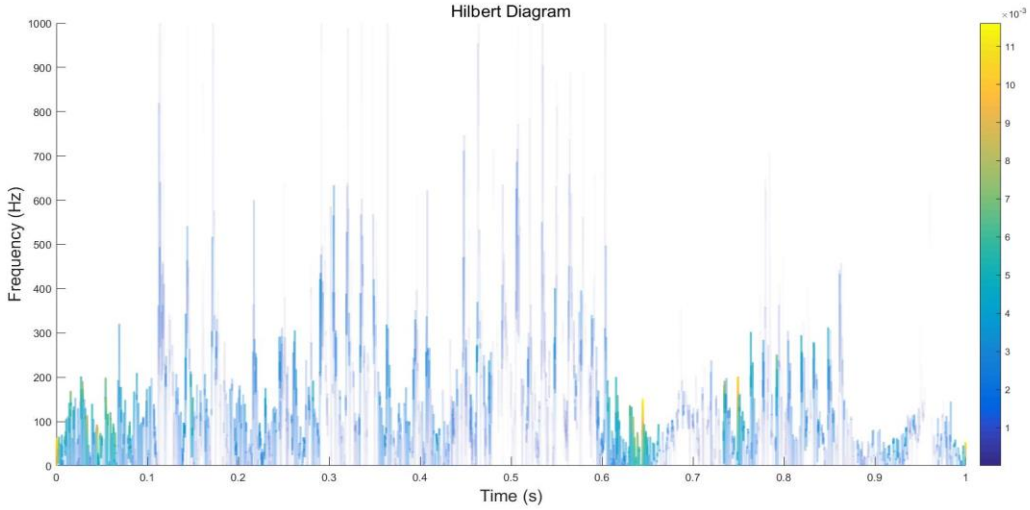

Figure 13. Hilbert Diagram of severe sputum stasis

As shown in figure 11, 12 and 13, the Hilbert Diagram shows the IMFs frequency change characteristics with time change. The color represents different amplitude of signals. The results illustrate that the after de-noise and empirical mode decomposition, the characteristics of original signals are almost kept. From above figures, mild sputum stasis and light severe sputum stasis results shows that the frequency of this two signals frequency concentrates in 0 to 200 Hz. For severe sputum stasis signal, although the frequency range is more wide than the other two signals, the high amplitude part still concentrate in 200 Hz below frequency range.

Wavelet Decomposition

Wavelet Decomposition (WD) is a signal decomposition method based on wavelet transform. The wavelet transform can be represented by the equation below:

$$CWT_f = \int_{-\infty}^{+\infty} f(x)\overline{\varphi(x)}dx \tag{15}$$

In the equation (9), $\overline{\varphi(x)}$ that represent wavelet mother function is

$$\overline{\varphi(x)} = |a|^{-\frac{1}{2}}\varphi\left(\frac{x-b}{2}\right) \quad a, b \in R \tag{16}$$

The a is the dyadic dilation and the b represent dyadic position.

Equation (11) is showing the Discrete Wavelet Transform:

$$DWT_f(c,d) = \int_{-\infty}^{+\infty} f(x)\varphi_{c,d}(x)dx = {a_0}^{-\frac{c}{2}} \int_{-\infty}^{+\infty} f(x)\varphi\left({a_0}^{-\frac{c}{2}}t - kb_0\right)dx \tag{17}$$

The DWT has high complexity for calculation. Then using the MALLAT algorithm to do the wavelet decomposition which is using for making the calculation easier. By using multi-resolution decomposition of the purpose signal, the coefficients can be obtained. [14,15]

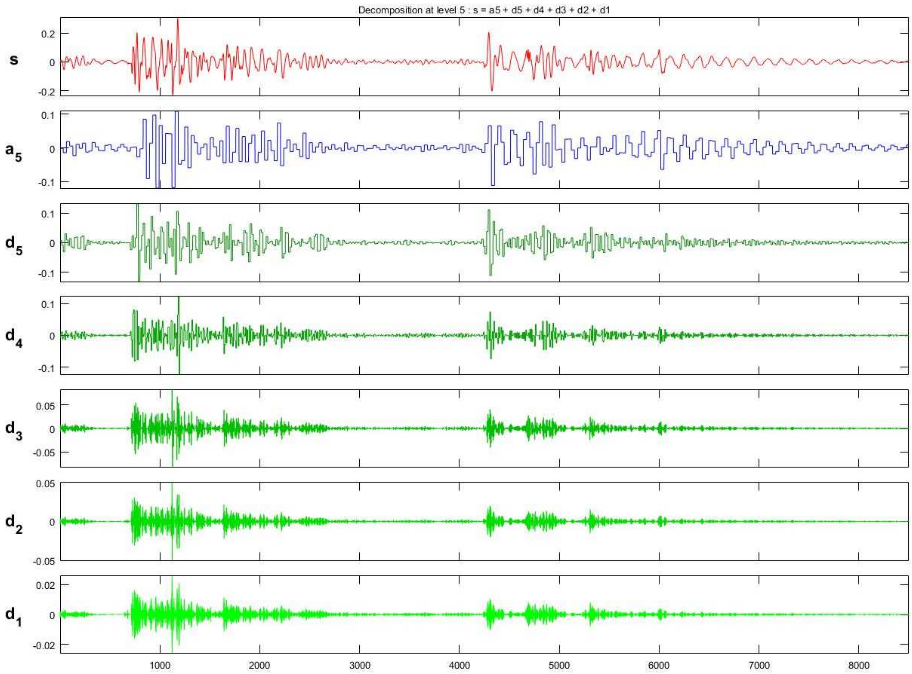

Figure 14. mild sputum stasis respiratory sound wavelet decomposition

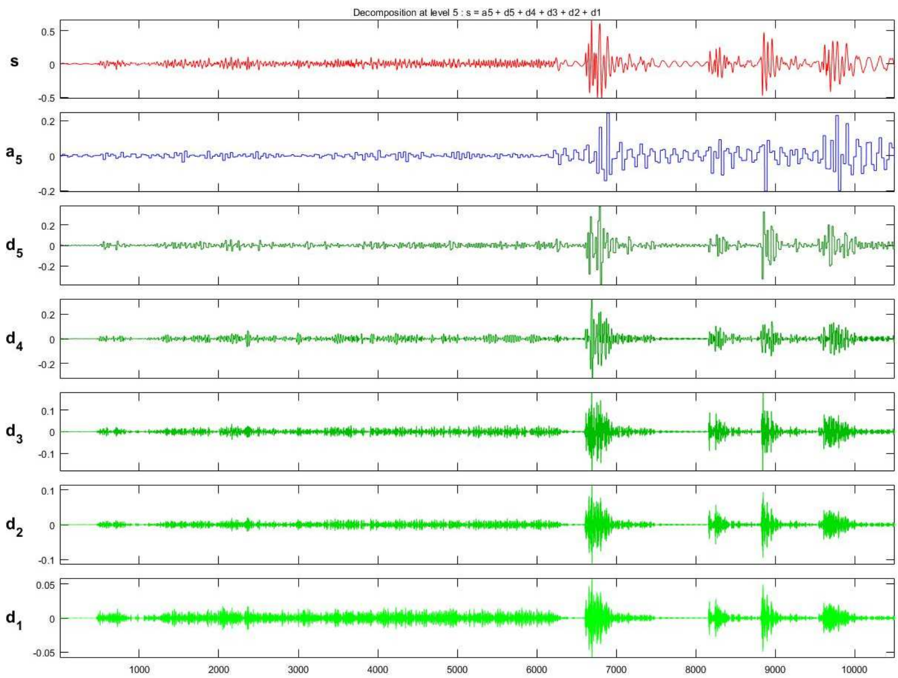

Figure 15. slight severe sputum stasis respiratory wavelet decomposition

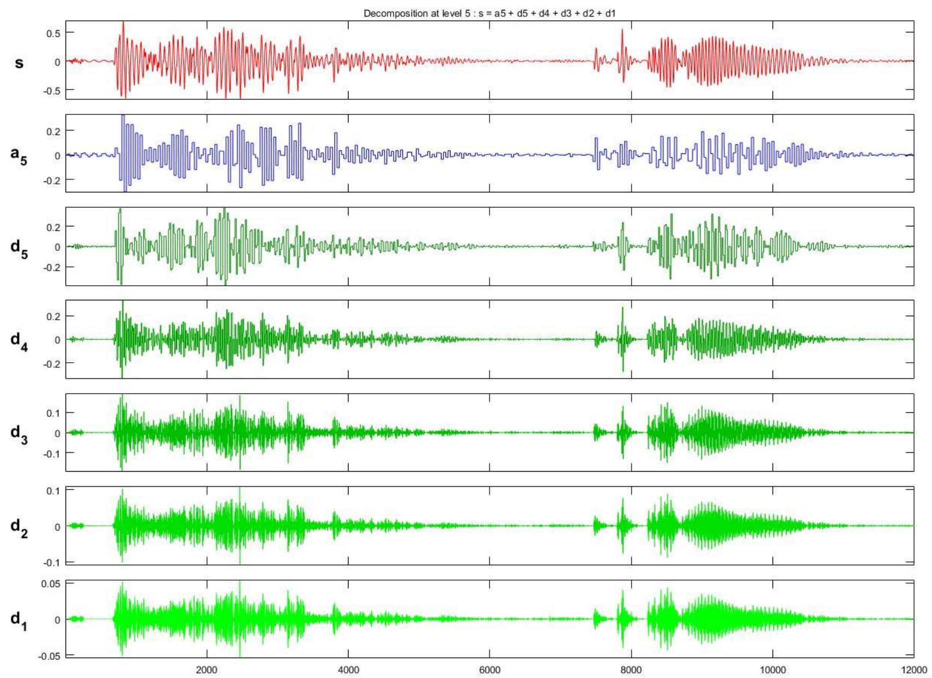

Figure 16. severe sputum stasis respiratory wavelet decomposition

The above figure 14 to 16 show the decomposition results of mild sputum stasis, slight severe sputum stasis and severe sputum stasis sound signals.

The disorder of the probability distribution of a random process can be measured by Shannon entropy as shown in following equation [16]

$$\mathrm{S}_{WT} = \sum_i p_i \ln\left(\frac{1}{p_i}\right) \tag{18}$$

p_i shows in the equation represent the probability of a random process.

If the p_i can be represented by Relative Wavelet Energy RWE), this entropy can define the disorder of the relative wavelet energy distribution. [17] The relative wavelet energy can be calculated by:

$$\mathrm{RWE}_i = \frac{WEN_i}{WEN_{total}} \tag{19}$$

The WEN_i in equation (13) is layer I wavelet energy and WEN_{total} is the total wavelet energy.

Thus, the Shannon entropy of relative wavelet energy of mild, slight severe and severe sputum stasis is showing in figure 17.

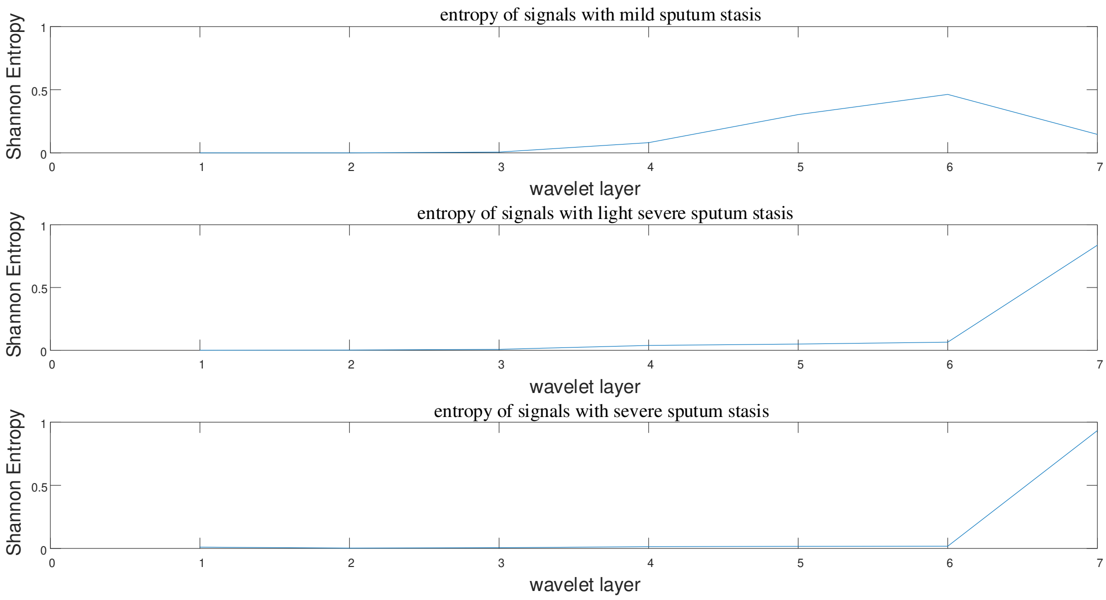

Figure 17. Shannon entropy of mild, slight severe and severe sputum stasis

As shown in the result, the RWE Shannon entropies of light severe and severe sputum stasis signal on the seventh wavelet layer are more than 85%. Thus, the most information of the signal is concentrated on layer 7. However, the mild sputum stasis signal has different information distribution. Thus, when it comes to signal analysis, the different distribution method can lead to hard to define the feature vector of the signal. In the contrast, the EMD method information distribution is concentrate on first 1 to 4 IMF, which has stable distribution.

Conclusion

In conclusion, this article is using spectrum subtraction de-noise method process three kinds of signals, mild sputum stasis, slight severe sputum stasis and severe sputum stasis sound signals. The spectral subtraction de-noise method has efficient effect in preprocessing respiratory sound. After preprocess, results of the three kinds of signals are decomposed by EMD and WD separately. The EMD results are transformed by Hilbert transformation function and the Hilbert diagrams showing the results that all the information of original signals is keeping well and concentrating in 200 Hz frequency range for EMD method. Results of WD were processed with Shannon entropy of RWE. In the end, the information of original signals over 85% is kept in layer 7 of wavelet transformation for light severe and severe signals, which cannot be analyzed well. It turns out that the EMD has better efficiency in preprocessing signals than WD.

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Reference

1. Fei Meng, Yan Shi, Na Wang, Maolin Cai, Zujing Luo, 'Detection of Respiratory Sounds Based on Wavelet Coefficients and Machine Learning', 2020, [J], Journal of Robotics & Machine Learning

2. Z. Moussavi, ''Fundamentals of respiratory sounds and analysis,'' Synth. Lectures Biomed. Eng., vol. 1, no. 1, pp. 1–68, Jan. 2006.
3. S. Reichert, R. Gass, A. Hajjam, C. Brandt, E. Nguyen, K. Baldassari, and E. Andrès, ''The ASAP project: A first step to an auscultation's school creation,'' Respiratory Med. CME, vol. 2, no. 1, pp. 7–14, 2009
4. M. Sarkar, I. Madabhavi, N. Niranjan, M. Dogra, Auscultation of the respiratory system, Ann. Thorac. Med. 10 (3) (2015) 158–168
5. E.Saatci, A. Akan, Heart sound reduction in lung sounds by spectrogram, in: IFMBE Proc, Vol. 11, 2005, pp. 1727-1983. No.1.
6. L.J. Hadjileontiadis, Empirical Mode Decomposition and Fractal Dimension Filter. IEEE ENG. Med. Biol. Mag. 26 (1) (2007) 30.
7. Emmanouilidou, D., McCollum, E.D., Park, D.E., Elhilali, M.'Adaptive Noise Suppression of Pediatric Lung Auscultations with Real Applications to Noisy Clinical Settings in Developing Countries'(2015) IEEE Transactions on Biomedical Engineering,62(9), 7084596,pp.2279-2288.
8. Haider Nishi Shahnaj. Respiratory sound denoising using Empirical Mode Decomposition, Hurst analysis and Spectral Subtraction[J]. Biomedical Signal Processing and Control, 2021, 64 : 102313.
9. Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen N-C, Tung C-C, Liu HH (1998) The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. R Soc 454:903–995
10. YANG H F, CHEN Y P P. Hybrid deep learning and empirical mode decomposition model for time series applications[J]. Expert Systems with Applications, 2019, 120(1): 128-138.
11. BOUNY L E, KHALIL M, ADIB A. Performance analysis of ECG signal denoising methods in transform domain[C]. International Conference on Intelligent Systems & Computer Vision, 2018 :1-8 .
12. Hossain I, Moussavi Z. An overview of heart-noise reduction of lung sound using wavelet transform based filter. In Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2003, 1: 458-461.
13. 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. 523–537, Sep. 2004
14. S. Mallat, A Wavelet Tour of Signal Processing. New York, NY, USA: Academic, 1999.
15. S. G. Mallat, ''A theory for multiresolution signal decomposition: The wavelet representation,'' IEEE Trans. Pattern Anal. Mach. Intell., vol. 11, no. 7, pp. 674–693, Jul. 1989.
16. C. E. Shannon, ''A mathematical theory of communication,'' ACM SIGMOBILE Mobile Comput. Commun. Rev., vol. 5, no. 1, pp. 3–55, 2001.
17. R. X. A. Pramono, S. A. Imtiaz, and E. Rodriguez-Villegas, ''Evaluation of features for classification of wheezes and normal respiratory sounds,'' PLoS ONE, vol. 14, no. 3, Mar. 2019, Art. no. e0213659.