Automatic picking method of microseismic signal first arrival time based on empirical wavelet transform

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Abstract. For problems in the process of microseismic signal acquisition, there is a large number of interference signals, which leads to that the first arrival time of signal is difficult to pick up. A picking method combines empirical wavelet transform (EWT) and signal first arrival algorithm is proposed to pick up the first arrival time of microseismic signal. Firstly, the component signals are obtained by the EWT method, which is used to decompose the microseismic signals with the characteristics of adaptive and conquering modal aliasing. Then the correlation coefficient and variance contribution rate of each component signals are calculated, and the component signals within the threshold range are selected for reconstruction to reduce the interference of noise signals. Finally, the modified energy ratio (MER) and fractal-dimension (FD) are used to pick up the first arrival time for the reconstructed denoising signal. According to the experimental verification, the accuracy of signal first arrival time picking combined with the MER and FD method based on EWT is 0.59% and 0.36% respectively. But in terms of efficiency, the former is obviously higher than the latter. The experimental and analytical results show that the model is highly accurate in picking up first arrival time of the effective signals and has a strong applicability to the signals of different data quantities.

1. Introduction
With the rapid development of microseismic monitoring technology, this advanced monitoring method has been applied to real-time online monitoring of mine slopes and geological disaster points [1]. Through analyzing the collected microseismic monitoring signals, safety assessment of rock mass stability is carried out. It is possible to predict the occurrence of various types of geological disasters and provide timely warning. However, the data collected in different application scenarios will contain a large number of interference signals, such as blasting vibration signals, mechanical vibration signals, electrical interference signals, etc. Therefore, the identification of rock fracture signals and the accurate first arrival time of signal picking have become the main problems that hinder the microseismic monitoring technology to feed back early warning information in time before disasters. It is one of the key technologies of security early warning to explore how to pick up the first arrival time of microseismic events accurately.
In the field of noise reduction of microseismic signals, some scholars have introduced empirical mode decomposition (EMD) and its improved methods applied into the processing and analysis of microseismic signals, etc. Gong Yue et al [2] used EMD to decompose the microseismic signals adaptively, and used the wavelet threshold method to denoise the high frequency IMF and reconstruct the denoised microseismic signals. Jia Ruisheng et al [3] proposed a microseismic signal denoising method based on EMD and independent component analysis, and the results show that the effect of noise reduction is obvious. Some people also applied wavelet transform and its improved methods to noise reduction. For example, Cheng Hao al [4] proposed a new layered adaptive threshold method based on wavelet transform, which can remove high-frequency noise signals and improve the signal-to-noise ratio (SNR) of mine microseismic signals. Cao Wei et al [5] used the method of wavelet packet decomposition and reconstruction to achieve the purpose of noise reduction of microseismic signals. Although this method has achieved certain effects, it still needs further improvement.

In the field of first arrival time picking of microseismic signals, there are many algorithms based on time domain, frequency domain and time-frequency domain [6~8]. The short and long time average ratio (STA/LTA) method proposed by R.V.Allen is the most widely used. This method obtains the position of first arrival by sliding long and short time windows and calculating the energy ratio of signals in the two time windows [9]. The energy ratio of the signal is used to obtain the position at the first arrival. Duan Jianhua automatically recognizes the microseismic effective signal based on the STA/LTA method, and achieves better application results [10]; The MER method developed from STA/LTA has the characteristics of higher picking precision and fast operation speed. In addition, Boschetti et al [11] first applied fractal dimension theory and digital images to the first arrival picking of microseismic signals in 1996. Zhao Guoyan et al [12] accurately identified the microseismic monitoring waveform, but there is no research on picking up the first arrival time of microseismic signal.

Aiming at the problems of low precision and difficulty in picking up the first arrival time of low SNR microseismic signals, this paper is based on previous research results and combined with the EWT algorithm, which has been widely used in signal field in recent years. These are applied to establish a model that can denoise microseismic signal and accurately pick up the signal primary arrival. EWT has been widely used in the field of signal denoising, such as wind turbine vibration signal denoising, seismic data noise suppression, etc [13~14]. Therefore, this paper first introduces the basic principle of EWT and first arrival picking of microseismic signals, and then analyzes the denoising effect of EWT reconstructed microseismic signal through simulation test data. Finally, the validity and applicability of the model proposed in this paper are verified by the actual microseismic signal.

2. Method and principle

2.1. The theory of empirical wavelet transform

EWT is a new method to construct adaptive wavelet proposed by Gilles [15]. It is similar to EMD in that it can adjust related parameters adaptively according to signal characteristics, but the EMD method is lacking in theoretical basis. However, the wavelet transform method can not divide the frequency band adaptively. Therefore, EWT is a signal analysis method combining the self-adaptability of EMD with the multi-scale feature of wavelet frame theory. The main idea is to split into different frequency bands adaptively according to the Fourier spectrum of the detected signal, and then construct appropriate orthogonal wavelet filter banks through the boundary of frequency bands. AM-FM components with tightly supported Fourier spectrum are extracted, and then the Hilbert transform is performed on the extracted AM-FM mode to obtain the meaningful instantaneous frequency and instantaneous amplitude. In turn, the Hilbert spectrum can be obtained [16]. The specific decomposition process and principle are as follows:

1. Firstly, Fourier transform is performed on the signal f(t), and the spectrum is obtained.
(2) The frequency band is divided according to the spectrum characteristics of the signal. It is assumed that the Fourier spectrum range \([0, \pi]\) of the signal \(f(t)\) is divided into \(M\), the number of discontinuous points is \(M+1\), and the boundary \(\omega_h\) of each frequency band range is a minimum value point between adjacent maximum. Suppose \(\Omega_M\) is a set of local minimum between \(\omega_{n-1}\) and \(\omega_n\), \(\omega_{n-1}=0\), \(\omega_M=\pi\), \(\omega_n = \arg \min \Omega_n\), the \(n\)th range can be expressed as \(\Lambda_n = [\omega_{n-1}, \omega_n]\), so it’s easy to get \(U_{n=1}^{M}\Lambda_n = [0, \pi], 1 \leq n \leq M - 1\).

(3) Constructing a wavelet filter banks. After the segmentation range \(\Lambda_n\) is determined, the empirical wavelet is defined as the band-pass filter on each range \(\Lambda_n\). The empirical wavelet is constructed according to the constructed Meyer wavelet and the Littlewood-Paley wavelet method. The formula (1) and (2) respectively define the scaling function \(\psi_n(\omega)\) and the wavelet function \(\phi_n(\omega)\) of the experience wavelet.

\[
\psi_n(\omega) = \begin{cases} 
1, & |\omega| \leq (1-\gamma)\omega_n \\
\cos \left[ \frac{\pi}{2} \beta \left( \frac{1}{2\gamma\omega_n}(\omega - (1-\gamma)\omega_n) \right) \right], & (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n \\
0, & \text{other} 
\end{cases} 
\]

\[
\phi_n(\omega) = \begin{cases} 
1, & (1+\gamma)\omega_n \leq |\omega| \leq (1-\gamma)\omega_{n+1} \\
\cos \left[ \frac{\pi}{2} \beta \left( \frac{1}{2\gamma\omega_n}(\omega - (1-\gamma)\omega_{n+1}) \right) \right], & (1-\gamma)\omega_{n+1} \leq |\omega| \leq (1+\gamma)\omega_{n+1} \\
\sin \left[ \frac{\pi}{2} \beta \left( \frac{1}{2\tau\omega_n}(\omega - (1-r)\omega_n) \right) \right], & (1-r)\omega_n \leq |\omega| \leq (1+r)\omega_n \\
0, & \text{other} 
\end{cases} 
\]

In the formula, the values of A and B use the following expression:

\[
\beta(x) = x^4 (35 - 84x + 70x^2 - 20x^3) \quad ; \quad \tau_n = \gamma\omega_n, 0 < \gamma < 1; \quad \gamma < \min_n \left( \frac{\omega_{n+1} - \omega_n}{\omega_{n+1} + \omega_n} \right) 
\]

(4) The filter bank decomposes the signal into different sets of AM-FM single components. According to the wavelet transform method to define the empirical wavelet transform \(T_f^\psi(n,t)\), the detail coefficients defined by formula (3) and the approximate coefficients defined by formula (4) are respectively expressed as follows:

\[
T_f^\psi(n,t) = \langle f(t), \psi_n(t) \rangle = \int f(\tau) \psi_n(\tau - t) d\tau = F^{-1} \left[ \hat{f}(\omega) \hat{\psi}_n(\omega) \right] 
\]

\[
T_f^\phi(n,t) = \langle f(t), \phi_n(t) \rangle = \int f(\tau) \phi_n(\tau - t) d\tau = F^{-1} \left[ \hat{f}(\omega) \hat{\phi}_n(\omega) \right] 
\]

EWT decomposes signal \(f(t)\) to get single component \(f_j(t)(j = 0, k; k = 1, 2, 3, \cdots)\) of AM-FM is shown in formula (5):
In the above formulas (1)–(5): $\psi_n(t)$ and $\varphi(t)$ are the scale function and the empirical wavelet function respectively, $\hat{\psi}_n(\omega)$ and $\hat{\varphi}(t)$ are the Fourier transform of $\psi_n(t)$ and $\varphi(t)$ respectively, $F^{-1}[\cdot]$ is the inverse Fourier transform, $\overline{\hat{\varphi}(\omega)}$ and $\overline{\hat{\psi}_n(\omega)}$ represent the complex conjugate of $\hat{\varphi}(\omega)$ and $\hat{\psi}_n(\omega)$ respectively, and $<\cdot,\cdot>$ represents the inner product. * is the convolution operation of the function.

2.2. Performance analysis of EWT algorithm

Through constructing the simulation signals to compare and analyze, it is verified that the EWT method can avoid the phenomenon of modal aliasing compared with the EMD method. The analytical expression of the simulated signal is:

$$\begin{aligned}
y_1(t) &= 0.3 \sin(20\pi t) \\
y_2(t) &= 0.5 \sin[86\pi t + 0.5 \cos(40\pi t)] \\
y_3(t) &= 0.25e^{-t} \cos(328\pi t) \\
y(t) &= y_1(t) + y_2(t) + y_3(t) + n(t)
\end{aligned}$$

In the formula (6), $n(t)$ represents white noise. It can be seen from the equation that the constructed signal mainly includes 10 Hz sinusoidal signal, frequency modulated signal with fundamental frequency of 43 Hz and modulation frequency of 20 Hz, and amplitude modulated signal with frequency of 164 Hz. The simulated synthetic signal is shown in Fig. 1. The sampling frequency $f_s$ is 500 Hz and the sampling time is 0.5 s. The SNR of the simulated signal after adding white noise is 6.2472.

![Figure 1. synthetic test signal](image)

The EMD decomposition result of the simulation signal and the Fourier transform result of each component are shown in Fig. 2 and Fig. 3 respectively. From Fig. 3, the 10 Hz sinusoidal components appear simultaneously in A3, A4, and A5, indicating that modal aliasing occurs, and there are severe modal aliasing among the remaining intrinsic mode function (IMF), failing to separate the specific frequency value signal from the components effectively.
Fig. 4 and Fig. 5 show the decomposition results of simulation signal by EWT and Fourier transform results of each component respectively. By comparing with the EMD decomposition results, the advantages of EWT resisting modal aliasing are obvious.

**Figure 2.** The figure of EMD decomposing the test signal

**Figure 3.** Fourier transform of the components of EMD

**Figure 4.** The figure of EWT decomposing the test signal
It can be seen from the Fourier transform results that A1 corresponds to the 10 Hz sinusoidal component in y1(t), A2 corresponds to the frequency modulated signal component with the fundamental frequency of 48 Hz in y2(t), A8 corresponds to the 164 Hz amplitude modulation in y3(t), and the rest of the signal components are generated by the noise signal. This shows that the EWT method can eliminate the problem of modal aliasing and extract modal components with definite physical meaning.

2.3. Methods for picking up the primary arrival of the signals

In the primary arrival picking method of microseismic signals, STA/LTA and weighting coefficient method based on STA/LTA are commonly used. However, the threshold setting has a great influence on the arrival time of microseismic events, the selection of long and short time windows also affects the recognition effect, and the algorithm is not efficient enough. In this paper, the MER method developed from the STA/LTA and the FD method are introduced. Although the MER method still needs to select the time window length, the algorithm has high efficiency and high precision for picking up signal with high SNR. The fractal dimension method has high picking precision but low efficiency. Therefore, these two methods have their own advantages and can organically integrate to complement the insufficiency of each other.

2.3.1. Modified energy ratio method. Firstly, the commonly used energy ratio method selects two time windows with the same length. Then the mutation point is found according to the energy difference between the front and rear time windows, which is considered as the first arrival point of microseismic signal. In the graph of energy ratio, the peak of the MER curve is the first arrival time of the microseismic signal [17]. The energy ratio formula of the front and rear time windows is as follows:

\[
z(i) = \left[ \frac{\sum_{j=-n}^{n} X(j)^2}{\sum_{j=-n}^{n} X(j)^2} \right]^{\frac{1}{2}}
\]

If \( j \leq 0 \), \( X(j) = \frac{[X(1) + X(2)]}{2} \); if \( j > N \), \( X(j) = \frac{[X(N-1) + X(N)]}{2} \); therefore, the calculation formula of the MER method is:

\[
Z(i) = \left[ X(i) \times z(i) \right]^3
\]
In the formula (8), $X(i)$ is the amplitude value of the microseismic signal at $i$, $n$ is the number of sampling points in the front and rear time windows, and $N$ is the number of samples of the microseismic signal.

2.3.2. Fractal-dimension method. FD is suitable for picking up the primary arrival time of local small data of microseismic signal. The main criterion for the primary arrival of the FD judgment signal is the change of the FD value, and the mutation point of FD value is the primary position of the signal. The first jump point of the "V" curve in FD graph is identified as the signal primary arrival point. In this paper, box counting dimension algorithm is used to calculate FD. The algorithm process is to divide the plane where the entire microseismic signal waveform is located by a square with the side length $\delta$. The number of squares that the microseismic wave will cross is $N(\delta)$, and the FD is obtained by taking the logarithm of $N(\delta)$ and $\delta$ [17]. The calculation formula for FD is as follows:

$$\text{FD} = \lim_{\delta \to 0} \frac{\lg \left[ N(\delta) \right]}{-\lg(\delta)}$$

That is, with $\lg(\delta)$ as the x-coordinate and $\lg[N(\delta)]$ as the y-coordinate. As the value of $\delta$ changes, the obtained points are fitted into a straight line by least squares method, and the slope value is the FD.

The specific steps of the model in this paper using the EWT to pick up the primary arrival of the microseismic signal are as follows:

1) To select the appropriate wavelet function and use the EWT algorithm to decompose the original microseismic signal $f(j)$ adaptively. The intrinsic modal component $f_0(j)$, $f_1(j)$, $\ldots$, $f_6(j)$, $\ldots$ of each frequency scale is obtained.

2) Calculating the correlation coefficient and variance contribution rate between the original microseismic signal $f(j)$ and the decomposed intrinsic modal component $C_i$. The relevant calculation formula is as follows:

$$R(i) = \frac{\sum_{j=1}^{n} (f(j) - \bar{f})(C_i(j) - \bar{C}_i)}{\sqrt{\sum_{j=1}^{n} (f(j) - \bar{f})^2} \cdot \sqrt{\sum_{j=1}^{n} (C_i(j) - \bar{C}_i)^2}}$$

$$V(i) = \frac{\sum_{j=1}^{n} \frac{1}{n} \sum_{j=1}^{n} C_i(j)^2 - \left(\frac{1}{n} \sum_{j=1}^{n} C_i(j)\right)^2}{\sum_{j=1}^{n} \frac{1}{n} \sum_{j=1}^{n} C_i(j)^2 - \left(\frac{1}{n} \sum_{j=1}^{n} C_i(j)\right)^2}$$

In (10) and (11), $R(i)$ is the correlation coefficient between $C_i$ and the original signal $f(j)$, $V(i)$ is the variance contribution rate of $C_i$, and $n$ is the total number of sampling points of the signal.

3) The intrinsic modal components reconstruction signal with correlation coefficient greater than 0.3 and variance contribution rate greater than 20% are selected, and the SNR of the reconstructed signal is calculated. If the SNR is not improved significantly, it is necessary to go back to step 1 and reselect the wavelet function and repeat the above steps.

4) MER and FD methods are used to pick up the primary arrival time of the reconstructed denoised signal. If the amount of signal data is more than 1000, it is recommended to use the MER method. On the contrary, the FD method is recommended.
3. Experimental analysis
In this paper, two models are used to test the proposed method. Model 1 is a synthetic signal that adds white noise to the artificially constructed signal. The purpose is to verify the effectiveness of EWT decomposition and reconstruction method for denoising signal with different SNR. Model 2 adds various random interference signals simulated by white noise to the effective microseismic monitoring signals. The accuracy and efficiency of the MER method and FD method are compared and analyzed respectively.

3.1. Model 1: EWT denoising analysis
The synthetic signal of the test model is shown in formula (12), where $\omega(t)$ is white noise. An effective signal is generated by this formula, which is a sinusoidal signal whose energy decayed exponentially with time. This test signal with different SNR is generated by changing the amplitude of white noise. The method proposed in this paper is reconstructed according to the correlation coefficient and variance contribution threshold, and it is found that the signal with different SNR has better denoising effect. It can be seen from Fig.6 and Fig.7 that the SNR of the signal has been significantly improved after denoising.

$$x(t) = 0.3e^{(-0.0075t+2.25)} \sin(0.05\pi t - 15\pi) + \omega(t)$$  (12)

The effective signal of low SNR is seriously covered by noise, and the local details at signal superposition are not obvious. While the background noise is removed by this method, the details of signal non-stationary characteristics are significantly improved, and the basic shape of effective signal is outlined. For the signal with high SNR, the amplitude fluctuation of the reconstructed signal after EWT decomposition is significantly reduced compared with the original signal, the local details and waveform change trend are consistent, and the reliability is higher.

![Figure 6. Synthetic signals with different SNR](image_url)

(a) -5.9078 (b) -3.9696 (c) -1.4709 (d) 2.0510 (e) 8.0716 (f) 20.1128
Figure 7. Reconstructing the denoised synthetic signal

(a) -0.4729 (b) 1.3965 (c) 3.7496 (d) 10.7452 (e) 13.7290 (f) 19.1829

3.2. Model 2: the first arrival time picking of microseismic signal

Effective microseismic signals superimposed with white noise are shown in Fig. 8, and its SNR is 2.2603. EWT and EMD methods are respectively used to decompose and reconstruct noisy microseismic signals. The results of reconstructing are shown in Fig. 9 (b) and (c). In order to compare the sketched details of reconstructed signals, effective microseismic signal, EWT reconstructed microseismic signal and EMD reconstructed microseismic signal are compared in Fig. 9. The closed area in red is the beginning part of the microseismic signal, the closed area in blue is the middle part of the microseismic signal, and the closed area in green is the end part of the microseismic signal. From the detail comparison, it can be seen that EWT signal has a good denoising effect after reconstruction. It accurately outlines the details of the signal, which is in good agreement with the original waveform. EMD signal reconstruction improves the SNR, but it is difficult to restore the signal form in many details. Therefore, there is a situation of error identification or large identification error in the process of picking up the first arrival of microseismic signals.

Figure 8. Original microseismic signal
**Figure 9.** Detail comparison of reconstructed signals

(a) Effective microseismic signal; (b) Reconstruction of signals by EWT method; (c) Reconstruction of signals by EMD method

**Figure 10.** Picking up the first arrival result with EWT method

(a) Reconstruction of microseismic signals by EWT method; (b) Picking up the first arrival with MER method; (c) Picking up the first arrival with FD method

**Figure 11.** Picking up the first arrival result with EMD method
(a) Reconstruction of microseismic signals by EMD method; (b) Picking up the first arrival with MER method; (c) Picking up the first arrival with FD method.

Fig. 10 and Fig. 11 show the results of picking up the first arrival of the microseismic signal reconstruction based on the EWT method and the EMD method respectively. The red circle is the time point of first arrival time. Comparing the first arrival results of the two microseismic signals, it can be seen from Table 1 that the pickup accuracy of FD is higher than that of MER. The relative errors of the two kinds of first arrival picking algorithms are 0.59% and 0.36% respectively, which can meet the needs of practical engineering applications. However, the algorithm efficiency of FD is significantly lower than the MER algorithm. In this experiment, there are 24,000 data of microseismic signals, which takes 4.917s to calculate by MER and 2302.546s to calculate by FD, and the efficiency of MER algorithm is 468 times that of FD. Therefore, in the case of a large amount of data, it is not appropriate to adopt the FD method, and the MER method can be adopted on the premise that the accuracy of the practical engineering application can be satisfied.

**Table 1.** First arrival results of microseismic signals are picked up by different models

|                                | Manual (ms) | MER (ms) | Relative error (%) | FD (ms) | Relative error (%) |
|--------------------------------|-------------|----------|--------------------|---------|--------------------|
| Original microseismic signal  | 5915        | 6715     | 13.52              | 6274    | 6.07               |
| Reconstruction signal by EMD  | 5915        | 5992     | 1.30               | 5985    | 1.18               |
| Reconstruction signal by EWT  | 5915        | 5950     | 0.59               | 5936    | 0.36               |

4. Conclusion

Aiming at the problem of picking up the primary arrival time in the microseismic monitoring signal with a lot of noise, a model based on EWT to decompose the original microseismic signal and reconstruct is proposed to achieve the purpose of denoising the microseismic signal. The results show that the effective signal and detail characteristics can be retained after denoising.

The method combines the EWT with two signal primary arrival picking algorithms. According to the characteristics of the algorithm, when the amount of data is large, the MER method should be adopted. On the contrary, the FD method should be used to pick up the primary arrival of the microseismic signal.

The processing results of actual microseismic signals are analyzed in this paper. When the signal is covered by noise, the method in this paper can still accurately pick up the primary arrival of the signal. It has proved the validity and applicability of this model method, and can provide accurate auxiliary forewarning information before the disaster.

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