Seismic signal denoising method based on CEEMD and improved wavelet threshold

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Abstract. Seismic data usually contains a lot of noise. In order to effectively remove noise and improve the signal-to-noise ratio of seismic signals, this paper proposes a method of combining complete empirical mode decomposition (CEEMD) with improved wavelet threshold denoising method. CEEMD has good adaptability to signal decomposition; the new wavelet threshold function can effectively overcome the discontinuity of hard threshold function and the deviation of wavelet coefficients in soft threshold function. The combination of the two methods can obtain better denoising effect. After processing the simulated signal with the method proposed in this paper, the signal-to-noise ratio is significantly better than the traditional single denoising method.

1. Introduction

Denoising is an important part of seismic signal processing, and wavelet transform is a common method of seismic signal denoising. In 1994, Professor Donoho DL and Johnstone of Stanford University proposed a denoising method based on wavelet transform, the wavelet threshold denoising method [1]. Wavelet threshold function is divided into hard threshold function and soft threshold function. It is generally considered that wavelet coefficients smaller than the threshold are produced by noise, and wavelet coefficients larger than the threshold are produced by effective signals. Therefore, the hard threshold function sets the wavelet coefficients smaller than the threshold to zero, which will cause the hard threshold function to step at the threshold point; the soft threshold function is to set the wavelet coefficients smaller than the threshold value to zero, and subtract the threshold value from the part greater than or equal to the threshold value. Although the continuity of the threshold function is ensured, the energy of the effective signal in the part with the wavelet coefficient greater than the threshold value will also be lost [2]. After wavelet threshold denoising, the signal processed by the hard threshold function will be rougher than the signal processed by the soft threshold [3]. Both threshold functions have their own advantages and disadvantages. Based on previous studies, this paper proposes an improved threshold function, which can flexibly adjust the threshold function through two parameters. It can not only ensure the continuity of the function at the threshold point, but also solve the problem of wavelet coefficient deviation.
Empirical mode decomposition (EMD) is a method for processing non-stationary signals proposed by Huang et al. in 1998, the method can adaptively decompose the signal into intrinsic mode function (IMF) according to the time scale characteristics of the signal itself, without setting any basis function in advance [4]. It can decompose a complex signal from high frequency to low frequency into a finite number of eigenmode functions, smooth the complex signal, and has better adaptability than wavelet functions [5].

Since the improved wavelet threshold denoising method and the EMD method have their own advantages and can deal with non-stationary signals well, this paper combines the two methods to propose a new seismic signal denoising method.

2. Materials and Methods

2.1. Wavelet threshold denoising process:
(1) Determine the appropriate wavelet basis function and decomposition level, decompose the wavelet coefficients under different levels. In this paper, coif5 is selected, and the decomposition level is 2
(2) Choose an appropriate threshold, this paper chooses the heursure threshold function;
(3) Selecting appropriate threshold function, the wavelet coefficients of each decomposition layer are improved wavelet threshold de-noising (when the wavelet coefficient is larger than the selected threshold value, it is considered that it is caused by effective signal and should be retained; when the wavelet coefficient is less than the threshold value, it is considered that it is generated by noise and should be eliminated);
(4) Perform wavelet reconstruction on the processed N-layer coefficients to obtain the denoised signal.

Calculate the threshold and select the threshold function
At present, there are four commonly used threshold selection methods: rigorousure threshold function, sqtwolog threshold function, heursure threshold function, minimaxi threshold function. Usually, the rigsure threshold function and minimaxi threshold function are relatively conservative. When the high frequency noise is less, the two thresholds can be used to extract the weak effective signal. However, sqtwolog threshold function and heursure threshold function are more thorough in denoising, which are more effective in denoising, but some effective signals will also be lost [6].

After calculating the threshold value, a threshold function is selected to process the wavelet coefficients. The traditional threshold function is divided into soft threshold function and hard threshold function.

The soft threshold function [7] is shown in formula (1).

\[
W_{j,k} = \begin{cases} 
\text{sgn}(W_{j,k})|W_{j,k}| - \lambda & |W_{j,k}| \geq \lambda \\
0 & |W_{j,k}| \leq \lambda 
\end{cases}  
\]

The hard threshold function [7] is shown in equation (2).

\[
W_{j,k} = \begin{cases} 
W_{j,k} & |W_{j,k}| \geq \lambda \\
0 & |W_{j,k}| \leq \lambda 
\end{cases}  
\]

Wavelet soft threshold function and hard threshold function have been widely used in denoising. However, the discontinuity of hard threshold function at the threshold point and the constant deviation of soft threshold function still affect the denoising effect. Therefore, on the basis of previous studies, this paper designs a new threshold function, which combines the characteristics of soft threshold function and hard threshold function, such as formula (3).

\[
W_{j,k} = \text{sign}(W_{j,k}) \times \left| W_{j,k} - \frac{\lambda}{\sqrt{|W_{j,k}|} + 1} + \frac{1}{e^{1/(\sigma |W_{j,k}|)}} \times (|W_{j,k}| \odot \lambda) \right| 
\]
In the formula, define operator \((A \odot B)\): when \(A\) is greater than or equal to \(B\), \((A \odot B) = 1\); when \(A\) is less than \(B\), \((A \odot B) = 0\), and the function image is shown in Figure 1.

![Figure 1. Improved threshold function](image)

This function has the following characteristics:

1. At the threshold point, the function is continuous, which overcomes the shortcomings of hard threshold function;
2. It satisfies the condition that it is an odd function;
3. By changing the parameters, the function can quickly approach the hard threshold function when it is greater than the threshold value, which can retain the energy of the effective signal.

2.2. EMD and CEEMD

EMD is an adaptive and efficient decomposition algorithm, which can decompose any complex data set into finite IMF, where IMF satisfies the following two conditions [8]:

1. In the whole data interval, the number of extreme points and the number of zero crossing points are equal or at most one difference;
2. At any point, the mean value of the envelope defined by the local maximum point and the envelope defined by the local minimum point is zero.

In order to alleviate the problem of refactoring, CEEMD performs the following operations:

1. Before decomposition, a group of noises with opposite signs are added to the original signal, and the amplitude of the new noise signal is the same each time.
2. After EMD decomposition of the noise-added signal, two sets of paired components containing opposite white noise are obtained.
3. Finally, the two complementary paired components are integrated to obtain the final eigenmode component, which eliminates the added noise.

3. Results & Discussion

In order to evaluate the effectiveness of this denoising method, the denoising effect of this paper is compared with other traditional single denoising effects. Firstly, a single channel synthetic seismic record is generated, and the Gaussian white noise with different decibels is added to the signal. Then, CEEMD denoising, wavelet denoising and joint improved denoising methods are used to denoise respectively, and the signal to noise ratio (SNR) evaluation results are calculated.

As shown in Fig. 2, the CEEMD of the noisy signal (the added Gaussian white noise is 19dB) is decomposed into seven layers, from high frequency to low frequency from top to bottom, and IMF7 is the residual component. It can be seen that the high frequency components IMF1 and IMF2 contain a
lot of noise, so the waveform is sharp and contains burr. Then the autocorrelation function of the noisy signal and the IMF component is calculated, as shown in Figure 3.

According to the comparison of the autocorrelation function, it can be seen that IMF2 is very different from the original signal. Therefore, it is determined that IMF1 and IMF2 contain a lot of noise and should be discarded during reconstruction. Figure 4 shows the result of CEEMD reconstruction after discarding IMF1 and IMF2. It can be seen that most of the noise is removed, but there is still a small amount of noise. Then the traditional soft threshold wavelet denoising (as shown in Fig. 5) and the proposed combined CEEMD and improved wavelet threshold denoising (as shown in Fig. 6) are compared.

Through calculation, when the added Gaussian white noise is 19DB, the SNR of the noise signal is 0.1152, the SNR after CEEMD denoising is 4.5136, and the SNR after wavelet denoising is 5.3004, combined with the SNR after denoising is 6.4335.

When adding different decibels of Gaussian white noise to the original signal, the statistics of the signal-to-noise ratio after denoising with different denoising methods are shown in Table 1. After comparison, the method proposed in this paper effectively improves the signal-to-noise ratio.
Figure 6. Combined denoising results (SNR is 6.4335db)

Table 1. The denoising effect of adding different decibel Gaussian white noise

| White noise of different energy (DB) | SNR of noisy signal | SNR of CEEMD denoising | SNR of wavelet denoising | SNR of combined denoising |
|-------------------------------------|---------------------|------------------------|--------------------------|--------------------------|
| 19                                  | 0.1152              | 4.5136                 | 5.3004                   | 6.4335                   |
| 21                                  | 1.7622              | 5.7448                 | 7.2026                   | 8.1195                   |
| 23                                  | 3.8109              | 7.8712                 | 8.5735                   | 9.6602                   |
| 25                                  | 5.9361              | 9.3089                 | 10.2133                  | 11.2964                  |

Through the above simulation processing of the signal, it can be seen that the combination of denoising methods in this paper can effectively improve the signal-to-noise ratio. The signal-to-noise ratio is higher than that of CEEMD denoising and wavelet soft threshold denoising alone, and the waveform is restored better, which proves the effectiveness of the combined denoising method proposed in this paper.

4. Conclusions

By improving the wavelet threshold function, this paper combines the advantages of the traditional soft threshold function and the hard threshold function, overcomes the shortcomings of the two functions, and proposes a new function that can adjust the threshold by changing the parameters, so as to retain the effective signal as much as possible while denoising. At the same time, this paper combines CEEMD with the improved wavelet threshold denoising method, and further improves the denoising effect by using the multi-scale adaptive decomposition characteristics of CEEMD. The calculation of the signal-to-noise ratio proves the effectiveness of the denoising method in this paper.

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