Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 12, No. 2, 2024

Research on the Application of CEEMD and CEEMDAN in Seismic Random Noise Suppression

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Abstract: Empirical Mode Decomposition (EMD) is an adaptive method for processing nonlinear and non-stationary data. Complementary Ensemble Empirical Mode Decomposition (CEEMD) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) are noise-assisted signal processing methods developed from EMD. During seismic data acquisition, various types of noise, including random noise, are inevitably captured, and current methods for dealing with such noise are limited. In this study, these two signal processing methods were applied in simulated experiments and real seismic data to suppress random noise. By analyzing the processing effects and runtime, it was found that CEEMDAN offers better processing performance and speed, making it a valuable tool for practical applications.

Keywords: Empirical Mode Decomposition; Seismic Data Processing; Random Noise Suppression.

1. Introduction

Due to the varying environments during seismic exploration, the collected seismic data often contain a significant amount of random noise. To minimize the interference of random noise on the effective signal, it is crucial to select a method that can effectively remove this noise.

Empirical Mode Decomposition (EMD) is a time-frequency analysis method for non-stationary signals proposed by Huang in 1998 [1]. Subsequent experiments have demonstrated its effectiveness in suppressing random noise. The method first decomposes the signal using EMD to obtain Intrinsic Mode Function (IMF) components, which are then reconstructed [2]. However, when the signal contains interference, EMD can produce mode mixing, a phenomenon that it inherently struggles to overcome [3]. This mode mixing can compromise the accuracy of the decomposition. The complexity of interference in real seismic data limits the effectiveness of EMD in seismic processing applications.

To address the shortcomings of the EMD method, Wu et al. proposed the Ensemble Empirical Mode Decomposition (EEMD) method, which adds Gaussian white noise as background noise to the original signal to solve the mode mixing problem in EMD[4]. However, the additional noise introduced by this method results in significant residual noise during reconstruction and lowers computational efficiency. This led to further developments, resulting in the CEEMD and CEEMDAN methods. The CEEMD (Complementary Ensemble Empirical Mode Decomposition) algorithm, proposed by Yeh et al., adds pairs of positive and negative white noise and sums the auxiliary white noise during the IMF calculation process, effectively addressing the residual noise problem caused by the added white noise in the EEMD method[5]. The CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) method, proposed by Torres et al., also effectively reduces computational costs [6].

CEEMD and CEEMDAN are two distinct methods developed to address issues encountered with EEMD, each with its own advantages and disadvantages. This paper focuses on studying the strengths and weaknesses of these two methods in seismic signal processing. By comparing the performance of CEEMD and CEEMDAN in handling seismic data, the paper summarizes the pros and cons of applying these methods to seismic signal processing.

2. Principles of the CEEMD Method

CEEMD builds upon EMD by adding pairs of positive and negative white noise. During the process of decomposing and selecting each IMF component, the corresponding positive and negative auxiliary noise is summed.

The first step is to add white noise $n_i(t)$ with amplitude a_0 to the original signal $S(t)$, resulting in a new signal:

$$S_i(t) = S(t) + (-1)^p a_0 n_i(t) \tag{1}$$

In which, p is the coefficient controlling the positive and negative noise, with $p = 0, 1$. i represents the number of times auxiliary white noise is added, with values $i = 1, 2, ..., M/2$.

In the second step, the EMD algorithm is applied to the new signal $S_i(t)$, resulting in a series of Intrinsic Mode Function (IMF) components $imf_{i,j}^{\pm}(t)$:

$$imf_j^+(t) = \frac{2}{M} \sum_{i=1}^{M/2} imf_{i,j}^+(t) \tag{2}$$

$$imf_j^-(t) = \frac{2}{M} \sum_{i=1}^{M/2} imf_{i,j}^-(t) \tag{3}$$

In the third step, the series of IMF components containing positive and negative auxiliary noise are added together correspondingly. Then, the N averaged IMF components are combined to obtain the final $imf_i, i = 1, 2, ..., j$. The detailed process of the CEEMD algorithm is illustrated in Figure 1.

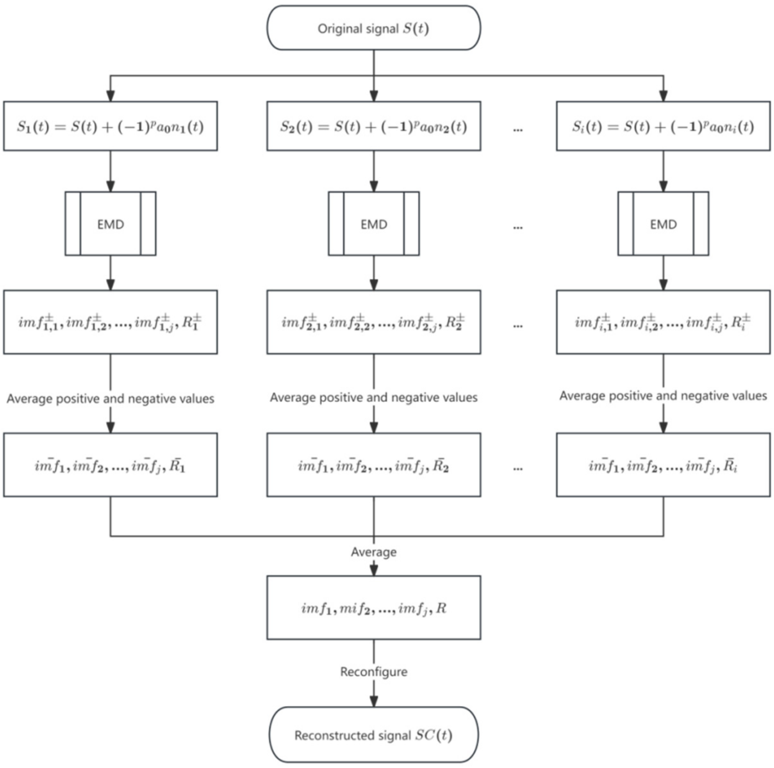


Figure 1. Flowchart of the CEEMD Process

3. Principles of the CEEMDAN Method

Unlike CEEMD, which directly adds auxiliary noise, CEEMDAN first decomposes the added auxiliary white noise using EMD before incorporating it into the IMF component decomposition process. In CEEMDAN, the first-order IMF component of the auxiliary white noise is added to the residual signal obtained after extracting the first-order IMF components $\overline{imf_1}(t)$, and then averaged to obtain the final first-order IMF component $\overline{imf_1}(t)$. After extracting this component, the resulting residual signal is used as the new input signal for further decomposition, continuing the iterative process to obtain the remaining IMF components $\overline{imf_1}(t)$ [7]. The process is as follows:

Step 1: Add Gaussian white noise to the original signal $S(t)$ to create a new signal:

$$S_i(t) = S(t) + \varepsilon n_i(t) \tag{4}$$

Where ε is the Gaussian white noise, $n_i(t)$ is the *i* th white Gaussian noise, $i = 1,2,...,M/2$. The M th first-order IMF component $imf_1^i(t)$ is obtained and the overall average is performed to obtain the final first-order IMF component $\overline{imf_1}(t)$:

$$\overline{imf_1}(t) = \frac{1}{M}\sum_{i=1}^{M} imf_1^i(t) \tag{5}$$

Step 2: Extract the first-order IMF component $\overline{imf_1}(t)$ from the original signal $S(t)$ to obtain the residual component $r_1(t)$:

$$r_1(t) = S(t) - \overline{imf_1}(t) \tag{6}$$

Add the first-order IMF component of the auxiliary noise $\varepsilon n_i{}'(t)$ to the residual component $r_1(t)$, and perform EMD decomposition:

$$r_1(t) + \varepsilon n_i(t) = imf_2^i(t) + r_2^i(t) \tag{7}$$

Where $imf_2{}^i(t)$ is the Gaussian white noise for the second iteration. Obtain second-order IMF components, then average them to get the final second-order IMF component $\overline{imf_2}(t)$:

$$\overline{imf_2}(t) = \frac{1}{M}\sum_{i=1}^{M} imf_2^i(t) \tag{8}$$

Using Equation (6), extract the second-order IMF component $\overline{imf_2}(t)$ from the residual component $r_1(t)$ to obtain the new residual component $r_2(t)$. Repeat this process iteratively to obtain the remaining IMF components $r_k(t)$:

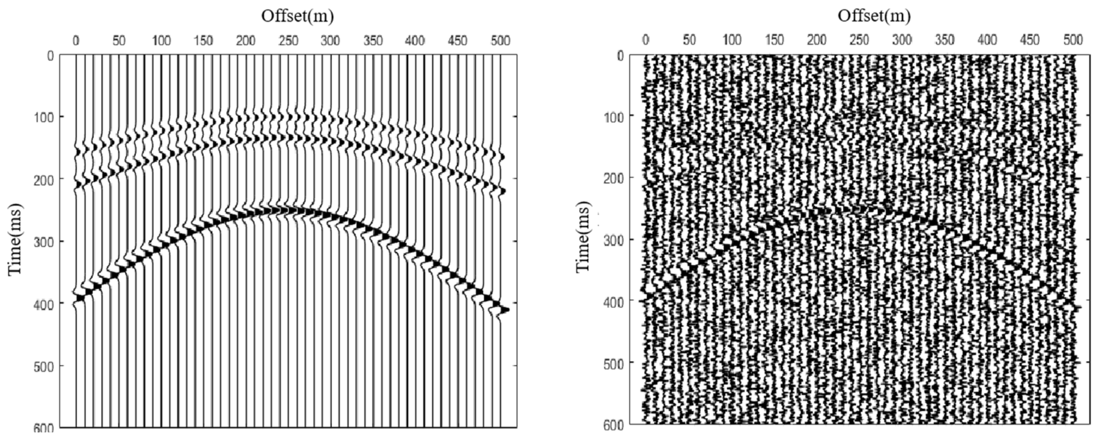
$$\overline{imf_{k+1}}(t) = \frac{1}{M}\sum_{i=1}^{M} imf_{k+1}{}^i(t) \tag{9}$$

$$r_{k+1}(t) = r_k(t) - \overline{imf_{k+1}}(t) = \frac{1}{M}\sum_{i=1}^{M} r_{k+1}{}^i(t) \tag{10}$$

Finally, reconstruct the processed signal by summing all the obtained IMF components, which is the final processed signal.

4. Simulation Data Analysis

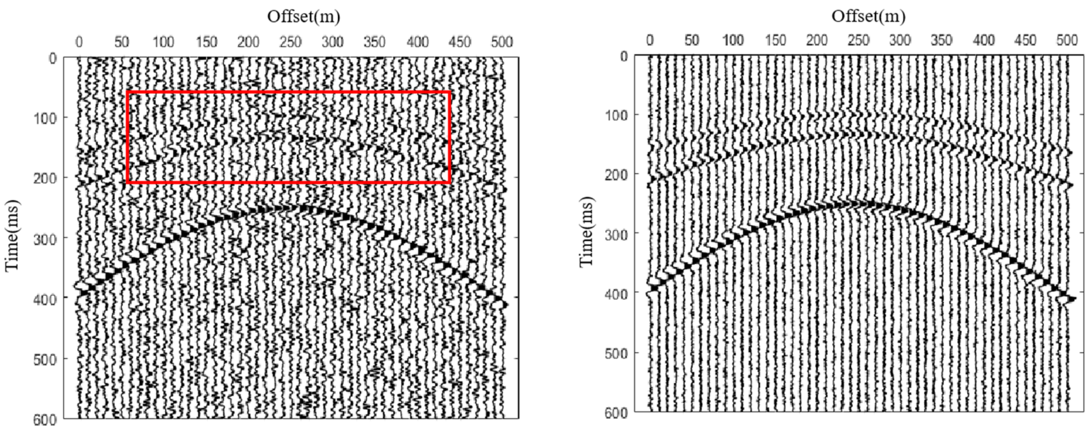
A forward modeling approach was used as illustrated in Figure 2. The forward record employed a Ricker wavelet with a dominant frequency of 60 Hz as the excitation wavelet. The maximum offset distance for the simulation was 500 meters, and the excitation time was 600 milliseconds. The simulated layer velocities were set as follows: v1=800m/s, v2=3000m/s, v3=6000m/s, v4=10000m/s. In Figure 2b, the signals from the first layer and the second reflection wave are covered and not clearly visible. The simulated noise intensity reflects real-world seismic exploration conditions.



a Simulated reflected wave seismogram b Simulate adding random noise to seismogram

Figure 2. Simulated seismogram

Figure 3 shows the random noise suppression of simulated seismic records using both the CEEMD and CEEMDAN methods. After processing the noisy simulated records with these two methods, the effective signal is clearly observable in both cases, with both methods achieving a certain degree of random noise suppression. Table 1 presents the signal-to-noise ratio and runtime for the results obtained from each method, allowing for a direct comparison. It is evident that CEEMDAN performs better than CEEMD in terms of both processing effectiveness and speed. CEEMD processing resulted in partial loss of the effective signal when it was covered by random noise (as shown in the red box in Figure 3a), whereas the effective signal after CEEMDAN processing showed no significant loss. CEEMD's denoising results left more residual random noise, with noticeable interference remaining, while CEEMDAN's denoising results had less residual random noise, resulting in less interference with the effective signal and a situation closer to one without random noise.



a CEEMD signal processing b CEEMDAN signal processing

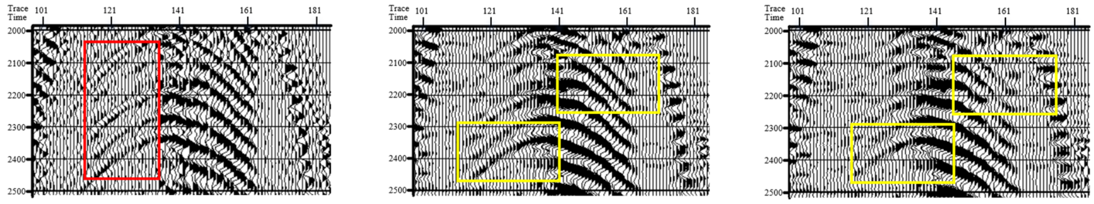
Figure 3. Analog signal after processing

Table 1. The two denoising methods correspond to signal-to-noise ratio

Denoising method	SNR	Denoising time/s
CEEMD	15.72	5.56
CEEMDAN	23.47	2.14

5. Analysis of Actual Data

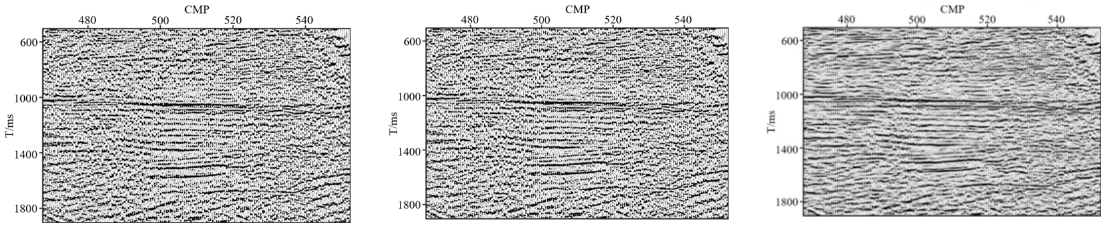
To validate the practical effectiveness of the two methods, both were applied to actual seismic data (Figure 4). The single-shot record before denoising was preprocessed to remove linear interference from surface waves, but it still contains significant random noise in the reflected waves (Figure 4a). In the red boxed area, the effective wave energy is weak, and random interference has had a considerable impact. After processing with CEEMD (Figure 4b) and CEEMDAN (Figure 4c), the random noise is suppressed in both cases, with the effective waves becoming clearer. The yellow boxed area shows that CEEMD causes slight loss in the restoration of the effective signal, which can affect subsequent processing results, although its noise suppression is still quite evident. CEEMDAN, with its better preservation of the effective signal, makes the effective waves more pronounced after suppressing the random noise.



a Single shot recording before denoising | b CEEMD single shot record after noise removal | c CEEMDAN single shot record after noise removal

Figure 4. Comparison of single shot record before and after denoising

To demonstrate the practical processing effects, the recorded data were processed using a uniform workflow to generate stacked profiles (Figure 5). The pre-processing stacked profile (Figure 5a) is characterized by incomplete continuity of the phase axes, with only some strong energy effective waves forming continuous phase axes, while most phase axes appear discontinuous, and complete phase axes cannot be imaged on either side. After denoising with CEEMD, the stacked profile (Figure 5b) shows improved continuity of the phase axes, though the improvement is not substantial. After denoising with CEEMDAN, the stacked profile (Figure 5c) shows enhanced clarity, with some layers becoming visible. Overall, the continuity of the phase axes is better compared to the CEEMD processing results.



a Overlay section before denoising | b CEEMD stack profile after de-noising | c CEEMDAN stack profile after de-noising

Figure 5. Stack section comparison before and after denoising

6. Conclusion

(1) Based on theoretical and practical analyses, the CEEMDAN method is superior to CEEMD for suppressing random noise in seismic data. The results obtained using CEEMDAN show a higher signal-to-noise ratio.

(2) From an algorithmic perspective, the CEEMD method operates with more independent steps compared to CEEMDAN, which frequently averages values. Therefore, CEEMD has more potential for improvement when combined with other methods.

(3) In terms of runtime, although CEEMDAN has a significant advantage over CEEMD, it is not as advantageous when applied to large datasets in practical scenarios. Both CEEMD and CEEMDAN require multiple iterations during computation, and further improvements are needed for their application in processing random noise in seismic data.

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