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Denoising method of acoustic emission and electromagnetic signals of rocks

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Abstract. *Nonlinear and non-stationary data are better analyzed with Hilbert-Huang Transform (HHT). Denoising signals are essential for various reasons. For better interpretation and improvement of signal quality and analysis of the non-stationary signals of acoustic emission and electromagnetic signals emitted by rocks, we introduce the CEEMDAN+Wavelet signal denoising algorithm using HHT, and the verified synthesized signal has demonstrated good results.*
Key words: *denoising algorithm, Hilbert-Huang transform, CEEMDAN+Wavelet*

Introduction

The Hilbert-Huang Transform (HHT) is a powerful tool for analyzing nonlinear and non-stationary data. It decomposes a signal into intrinsic mode functions (IMFs) using empirical mode decomposition (EMD), and then applies the Hilbert transform to each IMF to obtain instantaneous frequency information.

By incorporating HHT into the denoising process, we can potentially enhance the capabilities of CEEMDAN+Wavelet by better capturing the nonlinear and non-stationary characteristics of EEG signals. The combination could provide a more robust denoising approach, especially for EEG data that contains complex temporal dynamics [1]. In this paper, we introduce the novel method of CEEMDAN+Wavelet signal denoising algorithm.

Research methods

The measured signal of the research object in this paper has the characteristic of a jump change, therefore there will be the situation that the time scale is lost in the decomposition process, which leads to an uneven distribution of the extreme value points in the signal, and thus, the confusion of the decomposition, i.e., the situation of modal confusion.

The IMF components of each order obtained from the decomposition in this case are not physically meaningful. Therefore, here, the signal is decomposed by the method of Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) [2], which is based on the principle of adding white noise to cancel the noise mixed in the measured signal, thus alleviating the EMD.

In our study we use Spearman's rank correlation coefficient to select the IMFs obtained by CEEMDAN decomposition. The formula for calculating the Spearman rank correlation coefficient is shown in Equation (1):

$$\rho = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{1}$$

Results

To validate the feasibility and effectiveness of the denoising algorithm presented herein, the simulated AE signal and electromagnetic radiation data is processed by adding random Gaussian white noise. The decomposition layer in the wavelet thresholding algorithm is 4 layers and the function is sym8. The mathematical expression of the AE signal model is shown in Equation (2). The AE waveform (sampling frequency is 1 MHz) is given in Figure 1, which parameters are shown in Table 1. AE data which has Gaussian white noise with standard deviation of 0.3 is denoised by using different methods and the results are shown in Figure 1.

$$f(t) = \sum_{i=1}^{n} A_i e^{-Q_i(t-t_i)^2} \sin\left(2\pi f_i (t - t_i)\right) \qquad (2)$$

Table 1

Parameters of the synthetic signal

Parameter	Value
N	2
$\mathbf{A_1 = A_2}$	2
$\mathbf{Q_1}$	$6.14 * 10^8$
$\mathbf{Q_2}$	$1.28 * 10^8$
$\mathbf{t_1}$	$4 * 10^{-4}$s
$\mathbf{t_2}$	$5 * 10^{-4}$s
$\mathbf{f_1}$	80KHz
$\mathbf{f_2}$	50KHz

The SNR and RMSE are applied to compare the signal denoising effect, and since the noise is randomly generated, five sets of repeated experiments are done for comparison, and these results are shown in Table 2. We can deduce these two evaluation indexes that CEEDMAN+Wavelet method has better denoising effect in dealing with AE data with noise addition.

Table 2

Comparison of the effect of different denoising methods

SNR			RMSE		
Original signal (AE)	**Wavelet**	**CEEMDAN+Wavelet**	**Original signal (AE)**	**Wavelet**	**CEEMDAN+Wavelet**
5.1228	8.9428	10.6572	0.3073	0.1639	0.1473
5.1187	7.7583	10.1336	0.3074	0.1789	0.1538
5.4023	6.0087	7.9047	0.2975	0.2102	0.1910
5.4719	6.7554	9.6679	0.2951	0.1964	0.1634
4.9914	6.9252	9.3417	0.3119	0.1936	0.1671

The electromagnetic radiation data expression used in this study is presented in Equation (3). The signal-to-noise ratio and RMSE are also used to verify the five groups of noise-added electromagnetic radiation data, and the results are given in Table 3, which shows that the CEEMDAN+Wavelet method is more effective in dealing with noise-added denoising effect of electromagnetic radiation.

$$f(t) = 5(1 + \cos(18000\pi t)\ ) \quad \sin(20000\pi t) + 4\ \sin(10000\pi t) + 2\ \sin(15000\pi t) \quad (3)$$

Table 3

Comparison of the effect of different denoising methods

SNR			RMSE		
Original signal (EMR)	**Wavelet**	**CEEMDAN+Wavelet**	**Original signal (EMR)**	**Wavelet**	**CEEMDAN+Wavelet**
6.6701	8.8295	16.2739	2.4877	1.8013	0.8033
6.6047	9.5136	17.6659	2.5065	1.7739	0.7267
6.7783	9.1228	17.4489	2.4569	1.7996	0.7178
6.5991	8.9833	15.9022	2.5082	1.7822	0.8419
6.7540	9.0019	15.9166	2.4638	1.7864	0.8321

Conclusion

This paper presents a time-frequency method for analyzing rock measurement data by utilizing the Hilbert Huang transform in conjunction with CEEMDAN+Wavelet. The procedure, illustrated in Figure 1, involves several steps: firstly, denoising of the rock measurement data using CEEMDAN+Wavelet; followed by decomposition and Hilbert transform; and ultimately, obtaining the time-frequency-amplitude relation.

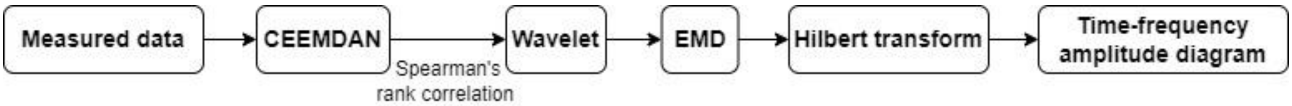

Fig. 1. Flowchart of the time-frequency analysis method

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