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Research paper

Cross-correlation analysis and time delay estimation of a homologous micro-seismic signal based on the Hilbert–Huang transform

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ABSTRACT

A micro-seismic signal's transient features are non-stationary. The traditional weighted generalized cross-correlation (GCC) algorithm is based on the cross-power spectrum density. This algorithm diminishes the performance of the time delay estimation for homologous micro-seismic signals. This paper analyzed the influence of calculation error on the cross-power spectrum density of a non-stationary signal and proposed a new cross-correlation analysis and time delay estimation method for homologous micro-seismic signals based on the Hilbert–Huang transform (HHT). First, the original signals are decomposed into intrinsic mode function (IMF) components using empirical mode decomposition (EMD) for de-noising. Subsequently, the IMF components and the original signals are analyzed using a cross-correlation analysis. The IMF components are subsequently remodeled at different scales using the Hilbert transform. The marginal spectrum density is obtained via a time integration of the remodeled components. The cross-marginal spectrum density of the two signals can also be obtained. Finally, the cross-marginal spectrum density is used in the weighted GCC algorithm for time delay estimation instead of the cross-power spectrum density. The time delay estimation is determined by searching for the weighted GCC function peak. The experiments demonstrated the superior time delay estimation performance of the new method for non-stationary transient signals. Therefore, a new time delay estimation method for non-stationary random signals is presented in this paper.

1. Introduction

The localization of original seismic activity is an essential micro-seismic monitoring technique. Accurate localization can explain the focal mechanisms of the seismic activity or evaluate disasters, such as rock burst. The time difference of arrival method is commonly used for micro-seismic source localization. In this method, the time difference immediately impacts the localization accuracy.

The arrival time difference of the signals acquired by different vibrational sensors is called the time delay. Typical time delay estimation methods include the generalized cross-correlation (GCC) method (Knapp and Carter, 1976; Souden et al., 2010), least mean square (LMS) method (Youn et al., 1982; Salvati and Canazza, 2013; Gedalyahu and Eldar, 2010), acoustic transfer function (ATF) method (Dvorkind and Gannot, 2003; Cornelis et al., 2010) and time–frequency energy method (Juliana, 2011). The GCC method is the most common. The method calculates the cross-correlation function between two homologous micro-seismic signals and later searches for the maximum peak. Accurate time delay estimations can be obtained for cases characterized by weak Gaussian noise. However, the performance declines in the case of low-SNR signals (Lee et al., 2014). Therefore, various improved techniques have been proposed, such as the ROTH filter (ROTH), smoothed coherence transform (SCOT), maximum likelihood (ML), ECKART filter (ECKART), Wiener filter (WP), phase transform (PHAT) and Hassab Boucher (HB) methods. Among these methods, the ML, ECKART, WP and HB methods can reach the Cramer-Rao low bound (CRLB) (Knapp and Carter, 1976; Davide et al.,2013), reducing the time delay estimation noise influence to a certain extent.

These methods are based on the second-order statistics theory and technology that comply with the Gaussian noise distribution characteristics. However, seismic signals and noise are non-stationary and non-Gaussian (Yue et al., 2012). Therefore, these methods significantly reduce the time delay estimation performance. This paper proposes a time delay estimation method based on the HHT to address the non-stationary characteristics of micro-seismic signals with noise. This method decomposes the micro-

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seismic signals using empirical mode decomposition (EMD) and sets reconstruction rules for the intrinsic mode function (IMF) to filter the high frequency noise. The marginal spectrum densities of the micro-seismic signals are then obtained via the Hilbert transform. The cross-marginal spectrum density is used in the weighted GCC algorithm instead of the cross-power spectrum density to estimate the time delay, thereby improving the time delay estimation performance.

2. Influence of non-stationary seismic signals on the GCC algorithm

2.1. Generalized cross-correlation time delay estimation algorithm

The seismic geophone acquisition of vibration signals is affected by external noise during the micro-seismic monitoring process, as shown in Fig. 1.

The $x_1(t)$ and $x_2(t)$ signals are received by the seismic geophones m_1 and m_2 and expressed as:

$$x_1(t) = s(t) + b_1(t) \tag{1}$$

$$x_2(t) = s(t-D) + b_2(t), \tag{2}$$

where $s(t)$ represents the original signal, D is the time difference between the two seismic geophones (m_1 and m_2) and $b_1(t)$ and $b_2(t)$ represent the external noise. In addition, $s(t)$, $b_1(t)$ and $b_2(t)$ are uncorrelated. The cross-correlation function between the micro-seismic signals $x_1(t)$ and $x_2(t)$ is subsequently represented as

$$R_{x_1x_2}(\tau) = E\left[x_1(t)x_2(t+\tau)\right] = R_{ss}(\tau-D) + R_{sb_1}(\tau-D) + R_{sb_2}(\tau) + R_{b_1b_2}(\tau) \tag{3}$$

where $E[\cdot]$ represents the mathematical expectation, R_{ss} is the auto-correlation function of the original signal and $R_{b_1b_2}$ is the cross-correlation function of additive noise from the two seismic geophones m_1 and m_2. It is assumed that $s(t)$, $b_1(t)$ and $b_2(t)$ are unrelated and completely orthonormal, yielding

$$R_{sb_1}(\tau-D) = R_{sb_2}(\tau) = R_{b_1b_2}(\tau) = 0 \tag{4}$$

Formula (3) can be rewritten as

$$R_{x_1x_2}(\tau) = R_{ss}(\tau-D) \tag{5}$$

The auto-correlation function is governed by $|R_{ss}(\tau-D)| \le R_{ss}(0)$. Thus, R_{ss} is maximized when $\tau - D = 0$. The time delay estimation between the two seismic geophones can now be expressed as

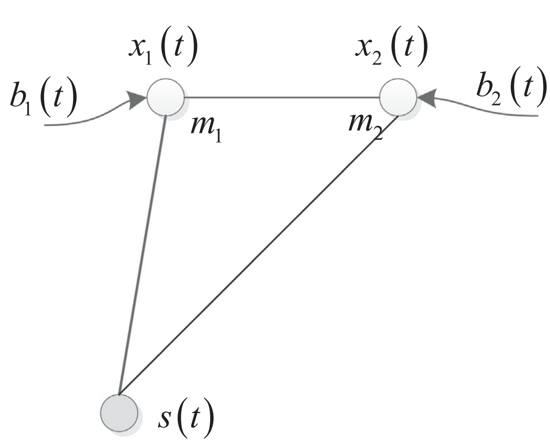

Fig. 1. Seismic geophone detects micro-seismic signals with noise.

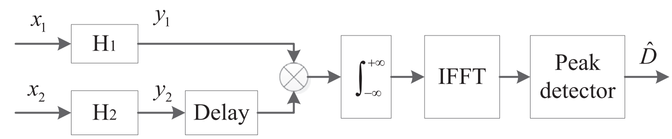

Fig. 2. Schematic diagram of the GCC method.

$$\hat{D} = \arg\max_{\tau}\left[R_{x_1x_2}(\tau-D)\right] \tag{6}$$

When the SNR is sufficiently large, the cross-correlation method can estimate the time delay by detecting the peak position of the cross-correlation function. However, the cross-correlation function does not work if background noise exists. The GCC method pre-filters the signals using the weighted function in the frequency domain before passing the signals to the correlator. This step whitens the signals and noise, accentuates the original signal and suppresses the noise power to improve the time delay estimation. The principle of the GCC algorithm is shown in Fig. 2.

As shown in Fig. 2, a generalized cross-correlation function can be defined as the Fourier inverse transformation of the weighted power spectrum density function.

$$R_{x_1x_2}^{(g)}(\tau) = F^{-1}\left[G_{x_1x_2}(f)\right] \tag{7}$$

$G_{x_1x_2}(f)$ can be expressed as

$$G_{x_1x_2}(f) = H_1(f)H_2^*(f)G_{x_1x_2}(f) \tag{8}$$

where * represents the complex conjugate and $G_{x_1x_2}(f)$ represents the cross-power spectrum density function of $x_1(t)$ and $x_2(t)$. The cross-correlation function of $x_1(t)$ and $x_2(t)$ can then be expressed as

$$R_{x_1x_2}^{(g)}(\tau) = \int_{-\infty}^{+\infty} H(f)G_{x_1x_2}(f)e^{j2\pi f\tau}df \tag{9}$$

where:

$$H(f) = H_1(f)H_2^*(f) \tag{10}$$

$H(f)$ is the generalized weighted function. Common generalized weighted functions include the SCOT, PHAT, ECKART and HB functions (Knapp and Carter, 1976; Joseph and Ronald, 1979; Wittlinger et al., 2007).

2.2. Error influence when calculating the power spectrum density of the time delay estimation algorithm

The GCC and improved-GCC algorithms are based on the phase difference of the power spectrum. The power spectrum density function is defined as

$$P_{xx}(\omega) = \frac{1}{N}\left|\sum_{n=0}^{N-1} x(n)e^{-j\omega n}\right|^2 = \frac{1}{N}|X_N(\omega)|^2 \tag{11}$$

where $P_{xx}(\omega)$ represents the power spectrum density and $X_N(\omega)$ is the Fourier transform for finite sequences $X_N(n)(n = 0, 1, 2, \ldots, N-1)$. In theory, the Fourier transformation can only be applied to stationary random signals, while micro-seismic signals are non-stationary and non-Gaussian. Therefore, a relatively large error will accrue during the power spectrum estimation process, which affects the precision of the time delay estimation. Modern power spectrum estimation techniques, such as the Welch, AR modeling, maximum entropy and Burg recursive methods, have improved the time delay estimation precision. However, these methods are all based on the Fourier transform. Fig. 3 shows the time delay estimation results for two micro-seismic signals utilizing the PHAT-GCC and SCOT-GCC algorithms,

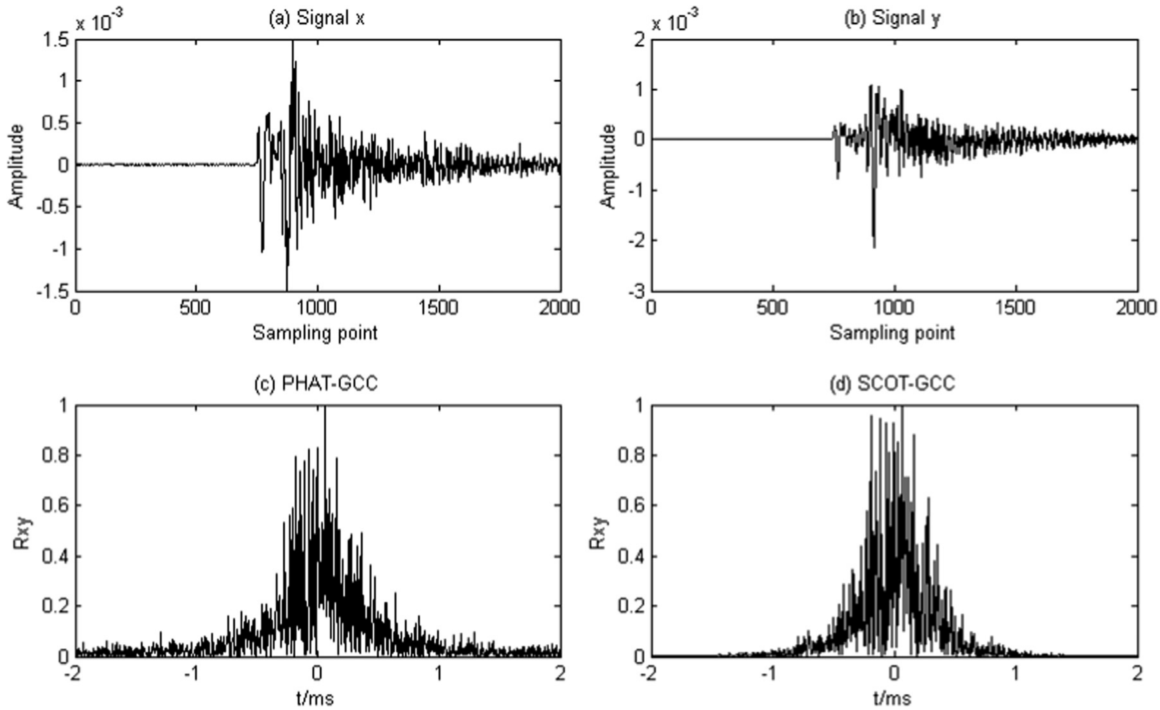

Fig. 3. Two homologous micro-seismic signal waveforms and time delay estimations based on different GCC methods.

where the signal length is 2000 and the sampling frequency is 1 kHz. In addition, the power spectrum density is calculated using the Welch method, the window function is given by the Hanning window for 512 sampling points and the number of overlapping sampling points of segmented sections of the signal sequence is 256.

The actual delay of signals x and y is 76 sampling points (0.076 s), and the estimations of PHAT-GCC and SCOT-GCC are 87 and 84 sampling points, respectively, as shown in Fig. 3. Both methods include considerable errors. The peaks in Fig. 3(c) and (d) are not sharp, and the anti-noise damping is significantly decreased. The main reasons for this error include: (1) this power spectrum estimation method is not suitable for non-stationary seismic signals, as it is based on the Fourier transform, which is applied to stationary signals. As a result, the time delay estimation based on the cross-power spectrum density includes considerable errors; (2) a large amount of external noise is included in the micro-seismic signal collection process. The noise reduces the precision of the time delay estimation.

This paper re-examines the non-stationary and non-Gaussian characteristics of micro-seismic signals, decomposes the signal with EMD, filters high frequency noise via IMF reconstruction, calculates the marginal spectrum density utilizing the Hilbert transform and estimates the time delay based on the cross-marginal spectrum density instead of the cross-power spectrum density used in the GCC algorithm. Thus, the time delay estimation precision is improved.

3. Time delay estimation algorithm based on HHT

The HHT is a new signal analysis technology proposed by N. E. Huang, which is suitable for processing non-stationary random signals (Huang et al., 1998). The approach is more adaptive for time-frequency localization analyses compared to Fourier transform and wavelet analysis methods (Chengwu et al., 2012). The HHT contains two parts, including an empirical mode decomposition (EMD) and Hilbert transform. This method has been widely used in seismic data processing, signal de-noising, fault diagnosis and other fields (Shadnaz et al., 2015; Wang et al., 2013; Jiang et al., 2013).

3.1. Principle of the time delay estimation algorithm based on HHT

The principle of this time delay estimation algorithm based on the HHT is shown in Fig. 4 for two homologous seismic signals. First, the two signals are decomposed into IMF components and ordered from high frequency to low frequency using EMD. The cross-correlation coefficients of each IMF and signal are then calculated to determine the signal and noise boundaries according to certain rules, so that the IMF noise can be rejected. The Hilbert spectrum of the remaining IMF is then calculated by utilizing the Hilbert transform. The marginal spectrum density is obtained via time integration of the Hilbert spectrum. Furthermore, the marginal spectrum density accumulates on the IMF to obtain the marginal spectrum density of the signal after de-noising. Finally, the cross-marginal spectrum density is used for time delay estimation instead of the cross-power spectrum density used in the weighted GCC algorithm. This weighted coefficient suppresses the noise and improves the time delay estimation.

3.2. Empirical mode decomposition and signal de-noising

EMD can decompose a signal into a series of IMFs with different time scales according to the characteristics of the non-stationary signals. These IMFs meet both of the following conditions (Sidorov, 2015): (1) the number of local extreme points is equal to or only one different from the number of zero-crossing points and (2) the mean value of the lower and upper enveloping curves, obtained via interpolation of the local maximum and minimum values, is zero. The EMD and signal $x(t)$ de-noising process is as follows.

Step 1: Search for the local maximum and minimum points on the time curve of the signal $x(t)$, fit the lower and upper enveloping curves three times using the spline function and calculate the mean lines $m_1(t)$ of the lower and upper enveloping

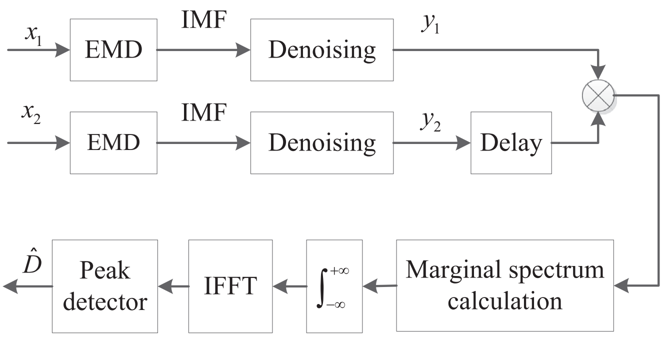

Fig. 4. Time delay estimation algorithm based on the HHT.

curves. $h_1(t)$ can be obtained via Formula (12).

$$h_1(t) = x(t) - m_1(t) \tag{12}$$

Step 2: Check that $h_1(t)$ satisfies the above two conditions. If satisfied, the first-order IMF of signal $x(t)$ is obtained, or $h_1(t)$ is considered as original signal and Step 1 is repeated.

$$h_{11}(t) = h_1(t) - m_{11}(t) \tag{13}$$

After k iterations, the stopping criteria for the iteration must satisfy the above conditions. The first-order IMF of signal $x(t)$ is then obtained and expressed as $c_1(t)$.

$$\begin{cases} c_1(t) = h_{1k}(t) \\ h_{1k}(t) = h_{1(k-1)}(t) - m_{1(k-1)}(t) \end{cases} \tag{14}$$

Step 3: Subtract $c_1(t)$ from the original signal $x(t)$ to obtain the residual $r_1(t)$.

$$r_1(t) = x(t) - c_1(t) \tag{15}$$

$r_1(t)$ is treated as a new signal to repeat Steps 1 and 2. A $c_i(t)$ series and residuals *res*, which did not continue to decompose, are obtained. The original signal can be expressed as

$$x(t) = \sum_{i=1}^{n} c_i(t) + \text{res}. \tag{16}$$

Step 4: With the n of IMFs obtained from the decomposition, the noise domination of the IMF gradually decreases, and the signal's domination strengthens according to the series $c_1(t)$, $c_2(t)$, …, $c_n(t)$. The method for determining the boundary between the noise and signal is as follows. First, the cross-correlation coefficients of each IMF and the original signal are calculated using formula (17)

$$R(x, c_i) = \frac{\sum_{t=1}^{N}\left(x(t) - \overline{x}\right)\left(c_i(t) - \overline{c_i}\right)}{\sqrt{\sum_{t=1}^{N}\left(x(t) - \overline{x}\right)^2}\sqrt{\sum_{t=1}^{N}\left(c_i(t) - \overline{c_i}\right)^2}} \tag{17}$$

N is the number of sampling points for signal $x(t)$

$$\overline{x} = \frac{1}{N}\sum_{t=1}^{N} x(t),\ \overline{c_i} = \frac{1}{N}\sum_{t=1}^{N} c_i(t) \tag{18}$$

The first local minimum is sequentially searched from the n cross-correlation coefficients obtained by Formula (17). The IMF corresponding to the first local minimum is the boundary between

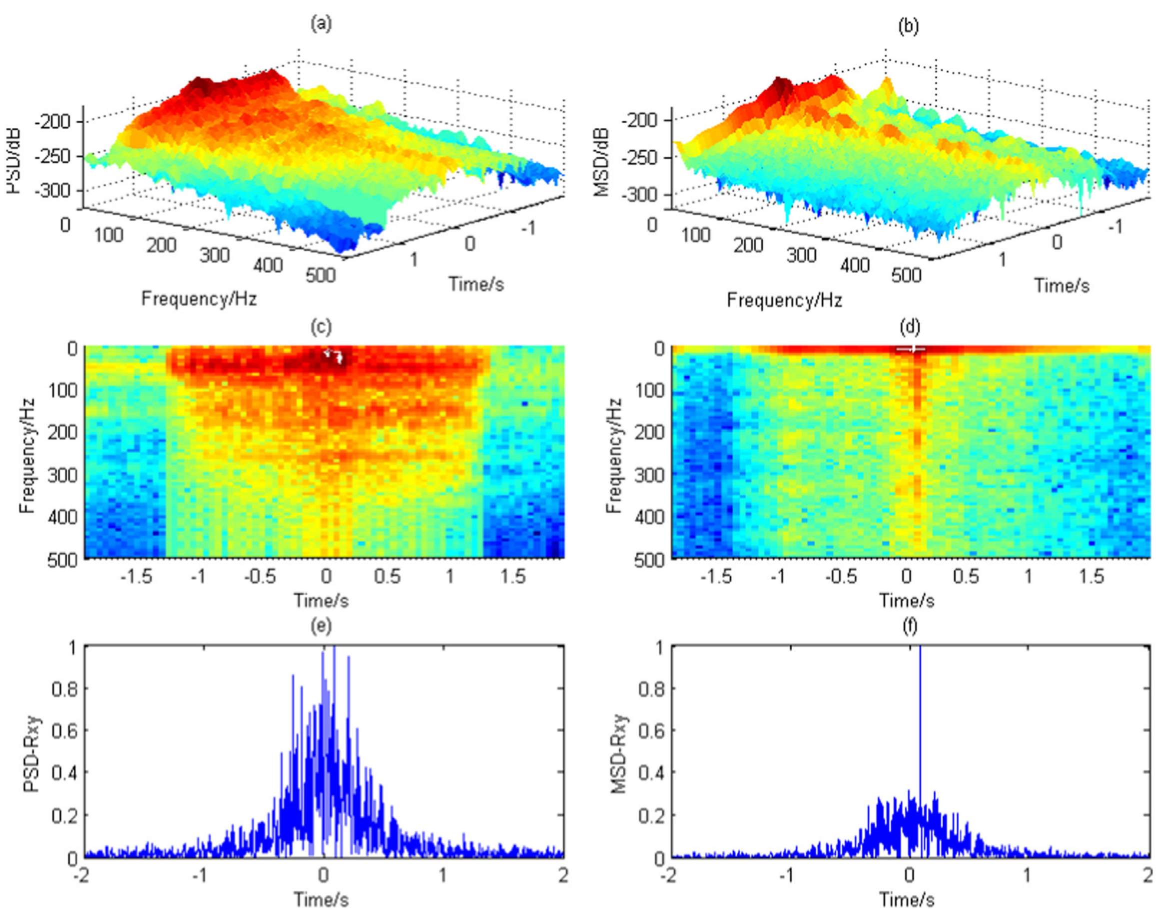

Fig. 5. (a), (c) and (e) illustrate the cross-power spectrum density, time-frequency spectrum of the cross-correlation function and normalized cross-correlation function based on PHAT-GCC; (b), (d) (f) and illustrate the cross-marginal spectrum density, time-frequency spectrum of the cross-correlation function and normalized cross-correlation function based on HHT-GCC.

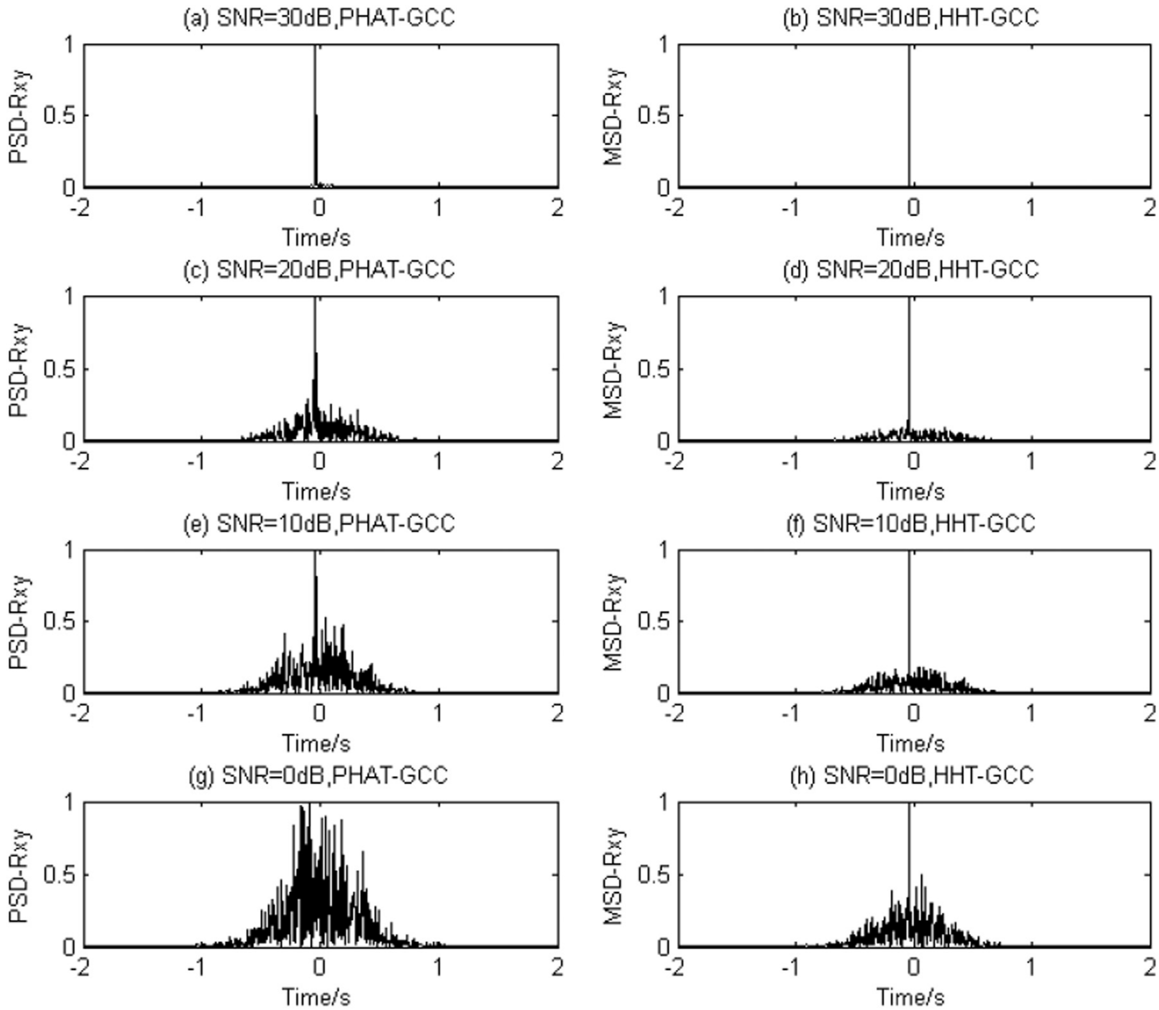

Fig. 6. Performance comparison of two time delay estimation algorithms for different SNRs.

Table 1
Comparison of time delay estimation accuracies for different signal-to-noise ratios.

SNR (dB)	Accuracy rate (%)	
	PHAT-GCC	HHT-GCC
30	84.44	100.00
20	77.78	100.00
10	55.56	97.78
0	37.78	91.11

the noise and signal (Li et al., 2013), denoted by $c_k(t)$. The previous $k-1$ IMFs are deleted and the remaining IMFs are reconstructed for signal de-noising. The post-de-noising signal can be expressed as

$$\hat{x}(t) = \sum_{i=k}^{n} c_i(t) + res. \tag{19}$$

3.3. Hilbert transform and marginal spectrum calculation

Each of the IMFs in formula (19) are transformed utilizing the Hilbert transform

$$H\left[c_i(t)\right] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{c_i(t')}{t-t'}dt' \tag{20}$$

The analytic signal can then be constructed via:

$$s(t) = c_i(t) + jH\left[c_i(t)\right] = a_i(t)e^{j\theta_i(t)} \tag{21}$$

where $a_i(t)$ is the instantaneous amplitude function, $\theta_i(t)$ is the instantaneous phase function and

$$a_i(t) = \sqrt{c_i^2(t) + H^2\left[c_i(t)\right]} \tag{22}$$

$$\theta_i(t)=\mathrm{arctg}\frac{H\left[c_i(t)\right]}{c_i(t)} \tag{23}$$

The instantaneous frequency can then be obtained.

$$\omega_i(t) = \frac{d\theta_i(t)}{dt} \tag{24}$$

The signal $x(t)$ after de-noising can be expressed as

$$\hat{x}(t) = Re\sum_{i=k}^{n} a_i(t)e^{j\theta_i(t)} = \mathrm{Re}\sum_{i=k}^{n} a_i(t)e^{j\int\omega_i(t)dt} \tag{25}$$

The expansion of formula (25) is called the Hilbert spectrum

$$H(\omega, t) = Re\sum_{i=k}^{n} a_i(t)e^{j\int\omega_i(t)dt} \tag{26}$$

The time integration of formula (26) is defined as the marginal spectrum density

$$h(\omega) = \int_0^T H(\omega, t)dt \tag{27}$$

The marginal spectrum density of signal $x(t)$ can be obtained after de-noising from formulas (26) and (27)

$$\hat{h}(\omega) = \int_0^T \mathrm{Re} \sum_{i=k}^{n} a_i(t)e^{j\int \omega_i(t)dt}dt = \sum_{i=k}^{n} \int_0^T a_i(t)e^{j\int \omega_i(t)dt}dt = \sum_{i=k}^{n} h_i(\omega) \tag{28}$$

where $h_i(\omega)$ represents the marginal spectrum density corresponding to the i-th IMF.

A marginal spectrum density calculation process analysis suggests that the marginal spectrum density statistically represents the accumulation amplitude distribution of each frequency point of the entire signal. Thus, the marginal spectrum density reflects the true frequency components of the signal and can be applied to non-stationary signals.

3.4. Weighted GCC algorithm based on marginal spectrum

The SNR of the micro-seismic signal is improved after EMD and de-noising. The marginal spectrum density is then used in the weighted GCC algorithm instead of the power spectrum density. The cross-marginal spectrum density of signals $x_1(t)$ and $x_2(t)$ can be obtained from formula (28)

$$\hat{h}^{(x_1x_2)}(\omega) = \hat{h}^{(x_1)}(\omega)\cdot\left[\hat{h}^{(x_2)}(\omega)\right]^* = \sum_{i=k}^{n} h_i^{(x_1)}(\omega)\cdot\left[\sum_{i=k}^{n} h_i^{(x_2)}(\omega)\right]^* \tag{29}$$

where $[]^*$ represents the complex conjugate. The weighted cross-marginal spectrum density function can be obtained from formulas (9) and (28)

$$R_{x_1x_2}^{(g)}(\tau) = \int_0^T H(f)\hat{h}^{(x_1x_2)}(2\pi f)e^{j2\pi f\tau}df \tag{30}$$

The marginal spectrum density is used to calculate the weighting coefficient $H(f)$ instead of the power spectrum density.

Strong external noises exist in the actual micro-seismic monitoring environment, increases the latter three expressions. A large error is produced by the assumption that $R_{x_1x_2}$ in formula (5) is approximately equal to R_{ss}. In this paper, the EMD and reconstruction have eliminated the majority of the high frequency noise effects. The weighting coefficient $H(f)$ in formula (30) can be improved based on Ma et al. (2004) to sharpen the associated peak and improve the time delay estimation precision

$$H'(f) = \frac{1}{\left|\hat{h}^{(x_1x_2)}(2\pi f)\right|^{\lambda}} \tag{31}$$

where $0.5 \le \lambda \le 1$ and λ changes as the SNR changes

$$\lambda = \begin{cases} \lambda_0, \ \sigma < \sigma_0 \\ \dfrac{\lambda_1 - \lambda_0}{\sigma_1 - \sigma_0}(\sigma - \sigma_1) + \lambda_1, \ \sigma_0 \le \sigma \le \sigma_1 \\ \lambda_1, \ \sigma > \sigma_1 \end{cases} \tag{32}$$

where σ represents the SNR, $\sigma_0, \sigma_1, \lambda_0, \lambda_1$ are constants that are based on the actual situation, and $\lambda_1 > \lambda_0$.

The improved weighted GCC function is as follows:

$$R_{x_1x_2}^{(g)'}(\tau) = \int_0^T H'(f)\hat{h}^{(x_1x_2)}(2\pi f)e^{j2\pi f\tau}df \tag{33}$$

4. Experimental results and analysis

The PHAT weighted generalized cross-correlation algorithm (PHAT-GCC algorithm) can reduce the side lobe and sharpen the main peak of the correlation function, improving the time delay estimation algorithm accuracy. The PHAT-GCC method is commonly used in practical applications and used to contrast the method proposed in this paper. The two waveforms in Fig. 3(a) and (b) are from the ISS Micro-seismic Monitoring System of China's eastern coal mine and are produced by homologous micro-seismic waves at a data acquisition frequency of 1 kHz. The previous 2000 sampling points of each waveform are chosen as the experimental samples and used to estimate the time delay, utilizing the PHAT-GCC algorithm based on the power spectrum density and the generalized cross-correlation algorithm (HHT-GCC algorithm) based on the HHT. In the PHAT-GCC algorithm, the power spectrum density is calculated using the Welch method, the length of the frame is 512 sampling points and the window function is a half-overlapping Hanning window. In the HHT-GCC algorithm, the signal is decomposed with the EMD toolbox (http://rcada.ncu.edu.tw/research1.htm) from the Research Center for Adaptive Data Analysis (RCADA) at Taiwan's Central University. The two algorithms are implemented in MATLAB, and the time delay estimation performance comparison is shown in Fig. 5.

The sharpness of the cross-correlation function peak reflects the precision of the algorithm, as shown in Fig. 5(e) and (f). The anti-noise performance of the HHT-GCC method increases after EMD de-noising and cross-marginal spectrum density calculations. Meanwhile, the normalized cross-correlation function peak is more prominent. The correct estimation can be obtained using 76 sampling points (0.076 ms). Fig. 5(a) and (b) illustrate the cross-power spectrum density and cross-marginal spectrum density distributions of the two signals. The distributions demonstrate that the signals and noise are effectively treated by the GCC method based on the marginal spectrum density. This method enhances the signals with a high signal-to-noise ratio and restrains the noise, improving the estimation's precision. A comparison of Fig. 5(c) and (d) suggests that the frequency components in the time-frequency spectrum of the cross-correlation function calculated using the proposed method are more centralized, creating a more prominent cross-correlation function peak.

The anti-noise performance of the algorithm proposed in this paper was further tested by adding non-Gaussian random noise to a seismic signal and conducting a computer simulation using different signal-to-noise ratios. First, a signal was selected with an obvious take-off point and high signal-to-noise ratio (SNR=30 dB). The sampling frequency was 1 kHz, and the length of the signal was 256 sampling points. The homologous signal was obtained after a delay of 20 sampling points, and the two signals with non-stationary random noises of different intensities were then analyzed via a cross-correlation analysis. PHAT was chosen as the weighted coefficient. The result is shown in Fig. 6. The non-stationary random noise is generated by the α-stable distribution model (Shao and Nikias, 1993) and the strength is calculated by formula (34)

$$E = \int_T |x(t)|^2 dt = \sum_{t=1}^{m} |x(t)|^2 \tag{34}$$

where $x(t)$ represents the signal amplitude, T represents the sampling period and m represents the sampling number.

Fig. 6(a) and (b) shows that the peaks of the cross-correlation function are both sharp, and both estimates suggest 20 sample points when the SNR=30 dB, demonstrating high precisions. The peak of the PHAT-GCC method cross-correlation function begins to expand as the signal-to-noise ratio decreases and several interference signals appear. However, the HHT-GCC method peak is also sharp. The results of the two methods are both correct, as shown in Fig. 6(c)–(f). The peak is submerged in the interference in the PHAT-GCC method results when SNR = 0 dB, while the peak remains sharp in the HHT-GCC method results. The HHT-GCC method result is also correct, although the interference increases.

45 groups of homologous signals were randomly chosen randomly from the mentioned ISS micro-seismic monitoring system to further verify the performance of the proposed algorithm. Non-Gaussian random noises with different intensities were added to these signals. The time delay estimation accuracies of the PHAT-GCC and HHT-GCC methods are compared for different signal-to-noise ratios. This paper defines estimates as differing when the error estimates vary from the true values by at least 5 sampling points. The accuracies are shown in Table 1.

As seen in Table 1, the method proposed in this paper results in a superior time delay estimation accuracy. Accuracy rates of at least 91.11% were maintained, even in a 0 dB strong noise environment. This method is suitable for the time delay estimation of micro-seismic signals and exhibits a strong anti-noise performance. The micro-seismic signals and external noise that signals contain are typical of random non-stationary signals. Generalized cross-correlation time delay estimation based on the power spectrum is unable to accurately estimate spectral distributions, which can lead to increased time delay errors. The proposed method is based on the HHT, which can process EMD noise reduction for micro-seismic signals with noise and random non-stationary characteristics. The marginal spectrum reflects the actual frequency components of the micro-seismic signals. Therefore, substituting the marginal spectrum for the power spectrum in the time delay estimation calculations ensures a high accuracy rate.

5. Conclusions

The micro-seismic signal's transient features are non-stationary. The cross-power spectrum density is widely used in traditional generalized cross-correlation algorithms to reduce the influence of external noise on the delay estimation accuracy. However, the cross-power spectrum estimation of non-stationary signals possesses a high uncertainty and exhibits poor performance when analyzing short signals. Therefore, the generalized cross-correlation algorithm based on the cross-power spectrum density is not suitable for non-stationary micro-seismic signals. The marginal spectrum density estimation based on the HHT can accurately reflect the signal distributions in the frequency domain. Thus, the cross-marginal spectrum density is used for time delay estimation instead of the cross-power spectrum density in the GCC algorithm. This substitution leads to a sharper correlation function peak for the homologous micro-seismic signals and improves the time delay estimation accuracy, even for non-stationary noises. The experimental results suggest that the method proposed in this paper is superior to the reference method.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.cageo.2016.03.012.

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