Estimation of TDOA with Cross Wavelet Analysis

Linqi Huang[1], Hong Hao[2], Xibing Li[3] and Jun Li[4]

1. Corresponding Author. Ph.D. candidate, School of Resources and Safety Engineering, Central South University, Changsha, Hunan 410083, China. & Centre for Infrastructural Monitoring and Protection, School of Civil and Mechanical Engineering, Curtin University, Bentley, WA6102
Email: linqi.huang@curtin.edu.au

2. Professor, Centre for Infrastructural Monitoring and Protection, School of Civil and Mechanical Engineering, Curtin University, Bentley, WA6102
Email: hong.hao@curtin.edu.au

3. Professor, School of Resources and Safety Engineering, Central South University, Changsha, Hunan 410083, China
Email: xbli@mail.csu.edu.cn

4. Lecture, Centre for Infrastructural Monitoring and Protection, School of Civil and Mechanical Engineering, Curtin University, Bentley, WA6102
Email: junli@curtin.edu.au

Abstract

This paper proposes a new method for calculating Time Delay of Arrival (TDOA) based on cross wavelet analysis. The cross wavelet transform is utilized to analyse the measured signals under micro-seismic events, and the cross wavelet power spectrum is used to measure the similarity of two signals in a multi-scale dimension and subsequently identify TDOA. The offset time instant associated with the maximum power of cross wavelet transform spectrum is the identified TDOA, and then the location of micro-seismic event can be determined. Individual and statistical identification tests are performed with measured data from an in-field mine. It is demonstrated that the proposed approach significantly improves the robustness and accuracy of micro-seismic source locating in mines compared to several existing methods, such as cross-correlation, multi-correlation, STA/LTA and Kurtosis methods.

Keywords: micro-seismic, time delay of arrival , cross wavelet transform

1. INTRODUCTION

Micro-seismic monitoring in mines is a common way to investigate and control mine disasters. It could predict the possible location of mine disasters by monitoring the vibration of mines in real time with arranged sensors. One major micro-seismic source locating method that has dominated the field for many years is based on estimating Time Delay of Arrival (TDOA). There are two different categories of automatic methods for the estimation of TDOA, namely, the absolute method and the relative method. The absolute method is based on picking up the absolute arrival time of the first arrival wave from different sensors. TDOA is obtained as the difference between the absolute arrival time instants (Jiao and Moon 2012, Wong et al. 2009, Munro, K.A. 2004, Han et al. 2010).

The relative methods do not require the detection of the absolute arrival time of measured waves. TDOA is obtained based on the similarity of two signals that are measured from the same source. The relative method is first developed in the field of analyzing the acoustic wave source (Knapp and Carter 1976). In a subsequent study that characterized the similarity of the waveforms by cross-correlation function, it was found that when the correlation value is the maximum, the time offset is most likely the time delay between the two analysed wave records (Carter 1987). In the recent two decades, the relative method has been applied widely in different areas (Jiang et al. 2013, Zhong et al. 2014, Nistor and Buda 2015, Huang and Jacob 2001), such as geophysics, seismology, acoustic, satellite navigation, radio, radar, sonar, and ultrasonics. Most of the relative methods for identifying TDOA, such as the double-difference algorithm (DDA) (Waldhauser and Ellsworth 2000), the generalized cross-correlation (GCC) (Knapp and Carter 1976) and generalized cross correlation with phase transform (GCC-PHAT) (Kwon et al. 2010), evaluate the similarity of two signals by means of the correlation function or cross covariance. The combination of cross-correlation function and Fourier transform allows the analysis of the signals in both the frequency and time domains (Knapp and Carter 1976, Carter 1987, Huang and Jacob 2001). This approach reduces the source location error to a certain extent, but it can only perform the analysis on the global scale. This limits the accuracy of the method in locating the micro-seismic source because one of the most prominent characteristics of micro-seismic signals is the non-stationarity and randomness (Xing et al. 2002, Correig and Urquizú 2002, Sobolev et al. 2005). A multi-scale analysis approach consisted of the wavelet transform and correlation function was proposed for identifying the TDOA from both the frequency domain and time domain (Kwon and Chan 1998). Wang and Chu (2001) decomposed the original acoustic signal into a series of time-domain signals, and then calculated the cross-correlation between the decomposed signals. This method analysed the signals in a specific frequency band, but the time-frequency information has not been fully used in the similarity analysis for the determination of the rubbing locations. However, those methods are subjected to the noise effect.

This paper presents a new approach for micro-seismic monitoring with cross wavelet transform. The cross wavelet transform is utilized to analyse the measured signals under micro-seismic events, and the cross wavelet power spectrum is used to measure the similarity of two signals in a multi-scale dimension and subsequently identify TDOA. Individual and statistical identification tests are performed with measurement data from an in-field mine. Identification results demonstrate and compare the robustness and accuracy of the proposed approach in locating micro-seismic source in mines with several existing methods such as, cross-correlation, multi-correlation, STA/LTA and Kurtosis methods.

2. THEORETICAL BACKGROUND OF TRADITIONAL METHODS

P-wave and S-wave are body waves travelling within the Earth. The difference in arrival time of waves can be used to locate a seismic event like an earthquake. P-wave has the highest velocity and is therefore usually the first wave to be recorded. Therefore, P-wave is generally used for micro-seismic monitoring in mines. Assuming that the travelling speed of the P-wave due to the micro-seismic event is constant in a homogeneous isotropic medium, Eq. (1) can be obtained for each sensor based on the fundamental theory of wave propagation

$$\sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} = v(t_i - t) \tag{1}$$

where (x_i, y_i, z_i) and (x, y, z) denote the spatial coordinates of the ith sensor and the micro-seismic source, respectively; v denotes the travelling speed of the P-wave; t and t_i respectively represent the time instants of the micro-seismic event and the arrival time of the P-wave at the ith sensor location.

Subtracting two equations corresponding to sensors *i* and *j* in the form of Eq. (1), Eq. (2) is obtained as

$$\sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} - \sqrt{(x_j - x)^2 + (y_j - y)^2 + (z_j - z)^2} = v(t_i - t_j) \tag{2}$$

The propagation speed of the P-wave and the spatial coordinates of those two sensors are usually available in practice. The most critical thing in solving Eq. (2) for determination of the seismic source coordinates is the accuracy of estimating the arrival time difference, which is TDOA. From Eq. (2), a hyperbola trajectory can be obtained with the two sensor locations 1, 2 as the foci, as shown in Fig. 1(a). The source location of the micro-seismic event must locate on the hyperbolic trajectory so it can be identified by examining the intersection of several hyperbolas. In planar space, at least two hyperbolas are needed to determine the source location, as shown in Fig. 1(b). In the same way, at least three hyperbolas are required to locate the micro-seismic event location accurately in a three-dimensional space. In other words, to determine the three unknowns x, y, and z in the parabola equation, three independent equations are needed to find the solution.

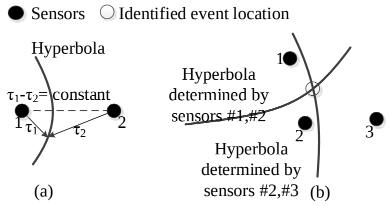

Fig. 1 The schematic illustration (a) a hyperbola determined by two sensors and their TDOA (b) micro-seismic event location identification with TDOA in a planar space

3. DEVELOPED APPROACH WITH CROSS WAVELET ANALYSIS

3.1 Theoretical Development

In this study, TDOA is identified with the cross wavelet transform. The theoretical background and development are presented here.

For a discrete signal *x(t)* (t = 1, 2,…, N), the continuous wavelet transform with regular time steps δt can be expressed as the convolution of *x(n)* with the scaled and normalized mother wavelet function

$$WT^x(u,s) = \sqrt{\frac{\delta t}{s}} \sum_{t=1}^{N} x(t)\psi_0\left[(t-u)\frac{\delta t}{s}\right] \tag{3}$$

in which u is the translation parameter, s is the scale parameter. The mother wavelet function is defined as Morlet wavelet because of its excellent balance between the time and frequency localization especially for characteristic extraction (Grinsted et al. 2004). The Morlet wavelet can be expressed as

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2} \tag{4}$$

where ω_0 is the wavenumber, in this case, ω_0=6. η denotes the non-dimensional time.

The cross wavelet transform of two signals *x(t)* and *y(t)* (t = 1, 2,..., N) is calculated as

$$WT^{xy}(u,s) = WT^x(u,s)WT^{y*}(u,s) \tag{5}$$

where "*" indicates the complex conjugation. The cross wavelet spectrum power is defined as $|WT^{xy}(u,s)|^2$. The complex argument $\arg(WT^{xy})$ can be interpreted as the local relative phase between *x(t)* and *y(t)* in time frequency space.

When using cross wavelet transform to identify TDOA between two signals x_i (i = 1, 2,..., N) and y_i (i = 1, 2,..., N), which are measured by two sensors S_1 and S_2 due to a micro-seismic event, it is assumed that TDOA between signals x_i and y_i is of k sampling steps, i.e. S_2 detects the P-wave arrival from the micro-seismic event $k*\delta t$ time instants after S_1 detects it. This means x_{i+k} (a delay with $k*\delta t$

time instants on the original signal) and y_i shall have an excellent similarity, and their cross wavelet spectrum power shall also reach the maximum. Based on this fact, the identification of TDOA between signals x_i and y_i is then transformed into an optimization problem to search for the k sampling steps corresponding to the maximum value of the following objective function,

$$f_{obj} = \max\left|WT^{x_{i+k}y_i}(u,s)\right|^2 \tag{6}$$

Wavelet transform has the edge effect due to the signal discontinuity, which may affect the transformed data. To overcome this, the Cone of Influence (COI) is introduced in the analysis. COI is a region of the wavelet spectrum with its shape similar as a cone. In this study, the area in which the cross wavelet spectrum power caused by a discontinuity at the edge has dropped to e^{-2} of the value at the edge.

The cross wavelet transform spectrum power within the above selected area and a significance level are calculated. The null hypothesis is defined for the wavelet power spectrum as follows. It is assumed that if a peak in the wavelet power spectrum is significantly above this background spectrum, it can be assumed to be a true feature with a certain percent confidence. For example, “significant at the 5% level” is equivalent to “the 95 confidence level”. The confidence level λ means that when Monte Carlo method is used to calculate the cross wavelet spectrum between background noises at one point in time-frequency domain, when the possibility of cross-correlation coefficient is less than 1-λ, the point belongs to the confidence interval λ. In the following sections, the result of *power* calculated is referred as cross wavelet spectrum power with a high confidence.

3.2 Identification Procedure

The flowchart of the proposed approach is shown in Fig. 2. Two signals from Sensors 1 and 2 are recorded from the same micro-seismic event source. Various processing steps will be applied.
Step 1: Two sensor signals $x(i)$ and $y(i)$ are acquired from the same micro-seismic event source in mines.

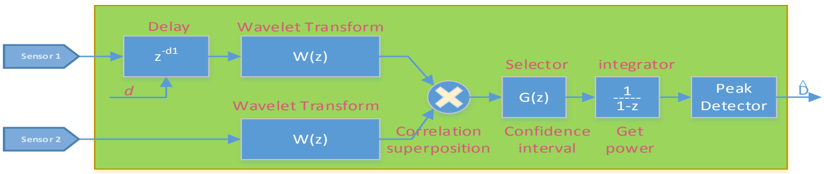

Fig. 2 The flow chart of the proposed approach with cross wavelet transform

Step 2: A series of time delay d_j is added to $x(i)$ respectively. Cross wavelet transform with Morlet wavelet function as previously mentioned is performed for two signals $x(i+d_i)$ and $y(i)$, respectively.
Step 3: Cross wavelet spectrum power is calculated by the above wavelet transforms in Step 2.
Step 4: After the cross wavelet transform calculation, the selector module is used for selecting the spectrum area Ω which has a high confidence. The integrator module is used to calculate the power of spectrum area Ω.
Step 5: Lastly, comparing the obtained cross wavelet transform power values from step 4 under different introduced delays d_j in previous steps, the time delay that leads to the maximum cross wavelet spectrum power is obtained as the TDOA between sensor signals $x(i)$ and $y(i)$. When more than three TDOA from several sensors are determined, the location of the micro-seismic event can be obtained with the available travelling speed of the P wave, which is usually measured in-site and assumed to be a constant value in this study.

4. MICRO-SEISMIC EVENT MONITORING WITH IN-SITU RECORDS

4.1 Site Conditions

The micro-seismic monitoring data used in this study were acquired from the Yongshaba mine in Kailin, Guizhou Province, China. The surface elevation of the phosphate mine is +1350 meters above the sea level, and the mining depth has reached to 700 m. The orebody is mainly brown phosphate rock, and the lithology is hard and compact. The density, tensile strength, uniaxial compressive strength, Young's modulus, Poisson's ratio, shear strength and internal friction angle are 3.22t/m^3, 4.46MPa, 147.89MPa, 29.21GPa, 0.25, 36.67 MPa, and 41.94°, respectively. The existence of more than twenty intensive faults and three dikes lead to the poor stability of Yongshaba mine, especially in the mining area under the Jin Yang highway, which is one of the key areas for micro-seismic monitoring. Considering the engineering geology in the mining area, the in-situ conditions and the available budget and equipment, a digital micro-seismic monitoring system with 32 channels developed by Integrated Seismic System (ISS) Company in South Africa was installed in the mine.

In total, twenty-eight sensors have been installed in this area, two of them are tri-axial sensors, denoted as T1 and T2, and placed at over 700m below the Yongshaba mine surface. The other twenty-six are single-axis sensors, which are numbered from 1 to 26, are evenly distributed in the three dikes #1, #2 and #3. The experimental data recorded by ten stable sensors, i.e. 1, 2, 3, 4, 8, 9, 12, 17, 18 and 22, are used to verify the proposed approach.

The statistical identification with measurements from multiple events is performed in section 4.2 to analyze the robustness and reliability of the proposed approach.

4.2 Statistical Verification

In this section, recorded data from ten sensors, namely No. 1, 2, 3, 4, 8, 9, 12, 17, 18, and 22, under five real micro-seismic events are analyzed. Any two of those ten sensors could be used to identify a TDOA, therefore forty-five TDOAs can be obtained under an event. For five separate micro-seismic events, two hundred and twenty-five TDOAs will be obtained totally and used for investigating the statistical identification accuracy with the proposed approach and those existing methods, i.e. cross-correlation method, multi-correlation method, STA/LTA method and Kurtosis method. When defining the parameters for these methods, the number of samples of the long term windows N_{LTA} and the short term windows N_{STA} are assigned as 1000 and 500 samples respectively in STA/LTA method. The length of the sliding window N is set as 200 samples for Kurtosis method.
The difference between the identified TDOA $\tau_{identified}$ and the reference TDOA τ_{ref} is defined as the absolute identification error as follows

$$\text{Absolute error in TDOA} = \left|\tau_{identified} - \tau_{ref}\right| \tag{7}$$

The mean value and standard deviation of the absolute identification errors are calculated. For a sequence $e_{i(i=1,\ldots,N)}$, the mean value and standard deviation are respectively calculated as

$$\mu = \frac{1}{N}\sum_{i=1}^{N} e_i \tag{8}$$

$$S = \sqrt{\sum_{i=1}^{N}\left(e_i - \mu\right)^2 \Big/ N - 1} \tag{9}$$

The statistical results of absolute errors of TDOA with different approaches are listed in Table 1. The mean value and standard deviation by the four existing methods and the proposed approach are listed, which are marked as A (Cross-correlation method), B (Multi-correlation method), C (STA/LTA method), D (Kurtosis method) and E (The proposed approach). Four additional artificial noise levels with Signal-Noise Ratio (SNR) =infinite (no noise effect), 20 dB, 10 dB and 5 dB are considered. For noisy cases, the extra noise effect is added to the originally recorded data to further verify the robustness of the proposed approach.

Table 1 Statistical results of absolute mean errors (M) and standard deviation errors (D) of TDOA (unit: ms)

Method SNR		+inf	20 dB	10 dB	5 dB
A	M	3.2	3.7	5.7	12.8
	D	5.6	6.5	7.3	18.5
B	M	2.4	3.7	5.1	11.6
	D	4.4	4.6	6.6	15.9
C	M	5.9	6.2	9.4	14.8
	D	8.2	12.5	16.1	23.3
D	M	3.1	5.7	8.5	14.3
	D	6.2	7.5	12.1	31.5
E	M	1.5	2.1	1.9	2.1
	D	2.1	2.7	3.2	3.4

Results in Table 1 demonstrate that the proposed approach gives the smallest mean value and standard deviation of the identification errors among all the five methods. The results also clearly show that the proposed approach is less sensitive to noise effect than the other four existing methods. Fig. 7 shows the box plot of the error analysis results. The bottom and top of the box denote the first and third quartiles, respectively, and the band inside the box denotes the mean value. The two ends of the dashed line represent the minimum and the maximum values of the absolute error. As shown in Fig. 7, the error of identification results with the four existing approaches, namely A, B, C and D, are obviously increasing with the severity of noise, indicating those methods are significantly affected by noise effect. The Kurtosis method is the most sensitive to the noise and then the Cross-correlation method. STA/LTA and the multiple-correlation methods have the similar performance to the influence of noise effect. The proposed approach is also affected by the noise in recorded signals, but at a less extent, indicating it is more robust compared with the other four existing methods.

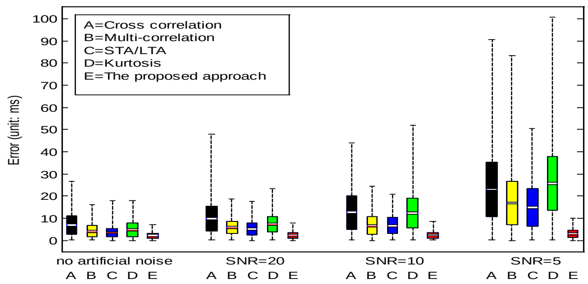

Fig. 7 Errors in TDOA of statistical identification results with different approaches

5. CONCLUSION

This paper proposes a new micro-seismic monitoring approach with cross wavelet transform. The proposed approach transforms time series into time-frequency domain and can achieve multi-scale analysis for a better identification of TDOA by cross wavelet transform and spectral analysis. The main idea and flowchart of the proposed approach are presented. The cross wavelet transform is utilized to analyse the measured signals during micro-seismic events, and the cross wavelet power spectrum is used to measure the similarity of two signals in a multi-scale dimension and subsequently identify TDOA. The offset time instant corresponding to the maximum cross wavelet transform spectrum power is identified as TDOA. Statistical verifications are performed with recorded data from a mine in China. The results demonstrate that the proposed method gives more accurate identification of micro-seismic TDOA, and is less sensitive to noise effect, as compared to the four other existing methods.

It is the first time that cross wavelet transform spectrum is used to identify TDOA. It not only preserves the advantage of traditional relative methods by avoiding the errors introduced by manually picking up the first arrival wave, but also utilizes the advantages of wavelet analysis methods, which provides a time-frequency multi-scale analysis. It has both frequency resolution and time resolution, which is of vital importance to analyse the nonstationary signals. Analysis results with in-situ measurement records demonstrate that the proposed approach outperforms other methods with a more accurate and reliable micro-seismic event TDOA identification result.

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