Blind Source Separation Method of Dual-Channel Single Vibration Signal Based on Power Spectral Density

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Abstract. In this paper, a convolution-mixing model of vibration signal is established according to the actual vibration signals collected by the sensor. This model is simulated and separated in P-waves and S-waves by using the frequency domain convolution blind source separation algorithm based on power spectral density matrix and diagonalization, and separated the vertical and horizontal waves of the actual two-channel underground vibration signals, which lays a technical foundation for the study of seismic characteristics and the inversion of source location.

Keywords: vibration signal, power spectral density, blind source separation.

1. Introduction

Blasting operations in underground mining activities such as coal mining and subway construction can easily cause microseismic events. The real-time monitoring of microseismic events has always been a hot topic for domestic and foreign scholars. The study of seismic phase identification of blasting shock waves is the basis of the seismic source location technology for blasting mining activities in underground coal mines.

In this paper, a convolution-mixing model of vibration signal is established according to the actual vibration signals collected by the sensor. This model is simulated and separated in vertical and horizontal waves by using the frequency domain convolution BSS algorithm based on power spectral density matrix and diagonalization, and separated the vertical and horizontal waves of the actual two-channel underground vibration signals.

Blind Source Separation (BSS) Theory can be used to separate the desired signals only by the observed mixed signals under the circumstance of lacking source signals and channel parameters even in completely unknown conditions, and can successfully distinguish the channel parameters while separating the signals to realize the location of the focus[1-2]. But at present, the research and application of blind source separation in the extraction of blasting vibration signals in seismic exploration is still in its infancy[3]. Yi et al., preliminarily discussed the application of independent component analysis in the separation of blasting signals through simulated signals to indicate its feasibility in the separation of blasting signals[5]. Zhang used the linear blind source separation algorithm based on time delay to make a preliminary attempt on the vertical and shear wave separation of multichannel simulated underground blasting vibration signals in a small region, which verified the feasibility of the BSS technology in the seismic phase identification of underground blasting vibration...
wave[6]. Xu et al. achieved the separation of the simulated primary wave and multiple wave in offshore oil and gas geological exploration by using ICA model[4].

2. Convolutional model for blind source separation

Due to the influence of propagation distance and geological conditions, the vibration signals detected by the sensor is the result of mixed superposition of various source signals with different delay in the process of vibration wave propagation. Therefore, the linear convolution hybrid model shown in the formula (1) is adopted.

\[ x(t) = A(t) * s(t) + n(t) \]  

Among them, it is assumed that the number of source signals and the number of observe signals are equal to n. Source signal is expressed as \( s(t) = [s_1(t), s_2(t), ..., s_n(t)]^T \) and the observed signal is expressed as \( x(t) = [x_1(t), x_2(t), ..., x_n(t)]^T \). The symbol * denotes a convolution operation. The noise signal is expressed as \( n(t) = [n_1(t), n_2(t), ..., n_n(t)]^T \), which is negligible at high SNR. \( A(t) \) is a hybrid filter with unknown source signals to sensors, which is the product of the transfer function equivalent to the propagation path of the source to the sensor and the transfer function of the sensor. For each channel, it can be represented by an L-order FIR filter. The above formula can also be written in vector form.

\[ x(t) = \sum_{\tau=0}^{L} A(\tau) s(t-\tau) \]  

Under zero initial conditions, corresponding to the z-domain is converted into the formula (3).

\[ X(z) = A(z) S(z) \]  

Where

\[
A(z) = \begin{bmatrix}
A_{11}(z) & \cdots & A_{1n}(z) \\
\vdots & \ddots & \vdots \\
A_{n1}(z) & \cdots & A_{nn}(z)
\end{bmatrix}
\]

\[ S(z) = [s_1(z), s_2(z), ..., s_n(z)]^T \]

Therefore, the observed signal is expressed as \( X(z) = [x_1(z), x_2(z), ..., x_n(z)]^T \). In the formula (4), \( A_\beta(z) = \sum_{\tau=0}^{L} a_\beta(\tau) z^{-\tau}, i \in \{1, ..., n\}, j \in \{1, ..., n\} \). \( a_\beta(\tau) \) is the coefficient of FIR filter, and the value range of each coefficient is generally in[0~1].[7]

3. Frequency domain convolution blind source separation based on joint diagonalization of power spectrum density matrix

Frequency domain convolution blind source separation algorithm based on power spectrum density matrix joint diagonalization utilizes the principle of instantaneous signal de-correlation blind source separation algorithm[8]. The diagonalization of instantaneous Power Spectrum density of the output signal of the Separation system, and the algorithm of parameter projection operator in frequency domain and the smoothness of separation filter in frequency domain are used to limit the length of
separation filter to solve the problem of permutation ambiguity in frequency domain. The steps of the algorithm are:

1. Preprocess the observed signal \( x'(t) \) : get \( x'(t) \) by removing the mean and whitening.
2. Initialize the separation matrix \( W \) and find the short-time Fourier transform \( W(\omega) \).
3. \( W(\omega) \) was updated by gradient descent method.
4. According to the power spectral density matrix combined with diagonalization of frequency domain convolution blind source separation algorithm to calculate the objective function \( J \);

\[
\min J = \sum_{\omega=1}^{K} \sum_{k=1}^{K} \|E(\omega, k)\|^2 \\
\text{s.t.} \|W\|^2 = 1
\]  

(6)

Where, \( E(\omega, k) \) is the estimation error.

5. The last time the objective function \( J^- \) was compared with \( J \), if \( J > J^- \), then quit, otherwise update \( J^- = J \), go to (3);
6. After exiting the update, we transform \( W(\omega) \) into \( W \) by inverse Fourier transform, and calculate the separation signal \( x = W \ast y \).

4. Dual-channel single blasting vibration signal convolution blind source vertical and horizontal wave separation simulation

4.1. Blasting vibration signal modeling

A single vibration wave mainly consists of a longitudinal wave (P wave) and a transverse wave. The transverse waves are divided into SH and SV waves. In the actual propagation process of vibration wave, due to the different location of the sensors, the transmission paths of the same vibration wave reaching different sensors are different, and the sensors’ own characteristic information are also different.

\( H(z) \) represents the propagation path from the source to the sensor, and it can also be represented by a \( L \)-order FIR filter. \( D \) represents the sensor characteristics. The mixed observation signals finally reaching the two sensors are:

\[
\begin{bmatrix}
X_1 \\
Y_1 \\
Z_1 \\
X_2 \\
Y_2 \\
Z_2 \\
\end{bmatrix} = \begin{bmatrix}
P \\
SH \\
SV \\
0 \\
0 \\
0 \\
\end{bmatrix} \begin{bmatrix}
H_1(z)D_1 & A_2(z) \\
H_2(z)D_2 & A_4(z) \\
\end{bmatrix} \begin{bmatrix}
x_1(t) \\
x_2(t) \\
\end{bmatrix}
\]  

(7)

In formula (7), \( \begin{bmatrix}
H_1(z)D_1 & A_2(z) \\
H_2(z)D_2 & A_4(z) \\
\end{bmatrix} \) is a hybrid matrix \( A(z) \) in a convolution blind source separation model, and it is a \( 6 \times 6 \) FIR filter matrix. The last three of the source signal is 0. The mathematical model (BELAID S et al., 2016) of the vibration signal is:

\[
s(t) = A_0 \left( e^{\frac{t}{\tau_1}} - e^{\frac{t}{\tau_2}} \right) n(t)
\]  

(8)
In formula (8), $A_2(z)$ and $A_4(z)$ are FIR filter matrices of $3 \times 3$. Since the latter three of the source signals are 0, the values of $A_2(z)$ and $A_4(z)$ will not affect the waveform of the observed signal generated. The values for $A_2(z)$ and $A_4(z)$ are set to a $3 \times 3$ matrix with a coefficient of 0. $D_1$ and $D_2$ are as follows:

$$D_2 = \begin{bmatrix}
\sin \alpha_{h}, \cos \beta_{h} & \sin \alpha_{sh}, \cos \beta_{sh} & \sin \alpha_{sv}, \cos \beta_{sv} \\
\sin \alpha_{h}, \sin \beta_{h} & \sin \alpha_{sh}, \sin \beta_{sh} & \sin \alpha_{sv}, \sin \beta_{sv} \\
\cos \alpha_{h}, & \cos \alpha_{sh}, & \cos \alpha_{sv}
\end{bmatrix}$$

(9)

$$D_1 = \begin{bmatrix}
\sin \alpha_{h}, \cos \beta_{h} & \sin \alpha_{sh}, \cos \beta_{sh} & \sin \alpha_{sv}, \cos \beta_{sv} \\
\sin \alpha_{h}, \sin \beta_{h} & \sin \alpha_{sh}, \sin \beta_{sh} & \sin \alpha_{sv}, \sin \beta_{sv} \\
\cos \alpha_{h}, & \cos \alpha_{sh}, & \cos \alpha_{sv}
\end{bmatrix}$$

(10)

The values in formula (9) and (10) are

$$\beta_{sv1} = \frac{5\pi}{14}, \alpha_{h1} = \frac{\pi}{6}, \beta_{h1} = \frac{\pi}{5}, \alpha_{sh1} = \frac{\pi}{7}, \alpha_{sv1} = \frac{\pi}{3}, \alpha_{h2} = \frac{\pi}{4}, \beta_{h2} = \frac{\pi}{5}, \alpha_{sh2} = \frac{\pi}{3}, \alpha_{sv2} = \frac{\pi}{3}, \beta_{sv} = \frac{\pi}{7}$$

So

$$D_1 = \begin{bmatrix}
0.4045 & 0.7802 & 0.3757 \\
0.2938 & 0.3757 & 0.7802 \\
0.8660 & 0.5000 & 0.5000
\end{bmatrix}$$

$$D_2 = \begin{bmatrix}
0.3535 & 0.4045 & 0.7802 \\
0.6124 & 0.2939 & 0.3757 \\
0.7071 & 0.8660 & 0.5000
\end{bmatrix}$$

(11)

Two FIR filters of $H_1(z)$ and are $A_2(z)$ generated by Matlab software, and the generated filters are as follows:

$$H_1(z) = 0.0375 + 0.2411 z^{-1} + 0.4465 z^{-2} + 0.2411 z^{-3} + 0.0357 z^{-4}$$

$$H_2(z) = 0.0288 + 0.143 z^{-1} + 0.328 z^{-2} + 0.328 z^{-3} + 0.143 z^{-4} + 0.0288 z^{-5}$$

(12)
Six observation signals are generated, as shown in Fig. 2.

![Figure 2. Two-channel single shock wave convolution mixed signal](image)

4.2. Simulation analysis of blind source and longitudinal wave separation

The hybrid generation observed signal is separated by the frequency domain convolution BSS algorithm based on the combined diagonalization of the power spectral density matrix. Set the algorithm parameters: The block length of FFT is 128. The impulse response length of the filter is 10. The learning rate is 1. The separation effect is shown in Figure 3. Before the separation, the signal interference ratios of the mixed signals were -2.28dB, -7.33dB and -9.75dB respectively. After separation, the signal interference ratios of the separated signals are 16.79dB, 19.31dB and 13.97dB, which are increased by 19.07dB, 26.64 dB and 23.72dB respectively. The similarity coefficients of separation signals corresponding to P-wave, SH-wave and SV-wave are 0.9891, 0.9522 and 0.9907 respectively. It can be seen that the method achieves the separation of vibration signals.

![Figure 3. Separation effect diagram](image)
5. Experiment

5.1. Analysis of actual vibration signal

5.1.1. Experiment procedure. In this experiment, a flat and wide field was selected to do the free-fall testing of shot in the same location at the same height. In this process, vibration sensors in the collecting system are buried in the ground along the propagation direction of the vibration wave, whose x-axis direction is consistent with that of the measuring line and the z-axis direction is vertical. Then arrange 2 measuring points and name them the measuring point 1 and 2. Because the source signal formed by the impact load in the shot free falling is difficult to obtain, the vibration waveform in x-axis direction of sensor in measuring point 1 is regarded as the source, and the waveform of the x-axis direction in measuring point 2 is considered as the vibration waveform obtained by the propagation of waveform in x-axis direction of sensor in measuring point 1 through a certain distance. At the same time, record the vibration waveform of measuring point 1 and 2.

5.1.2. Vibration signal analysis. According to the power spectrum and the time-frequency diagram of vibration signal, it will find the main frequency of vibration wave and its corresponding time range, as shown in Figure 4 and Figure 5(a~f).

![Figure 4. Actual vibration signal power spectrum](image)

(a) Time frequency diagram of X1  (b) Time frequency diagram of Y1  (c) Time frequency diagram of Z1
Fig. 5. (a~f) Actual vibration signal time frequency diagram

Fig.4 and Fig.5 show that there are three main frequency of vibration wave 60Hz, 90Hz and 140Hz, which indicates that the vibration wave is composed of at least three waves of different frequencies. The power spectrum and time-frequency diagram show that the energy of the vibration wave on the x-axis of the sensor 1 is mainly concentrated in the low-frequency region of 60~100Hz and two frequencies of higher energy is 60Hz and the 90Hz. Y-axis vibration wave includes two frequencies, but the energy of the wave is mainly concentrated in about 60Hz. On the Z-axis, there are two frequencies with higher energy 100Hz and 140Hz, which indicate that the wave on the Z-axis is generated by two waves, and the energy of the vibration wave on X, Y, Z axes of sensor 2 is mainly concentrated in the low frequency region of 60Hz. Thus it can be seen that the wave signals collected by two sensors are mixed by waves of 60Hz, 90Hz and 140Hz.

5.2. Vertical and horizontal wave separation of blasting vibration signal

The actual vibration signal is separated by the frequency domain convolution BSS algorithm based on the combined diagonalization of the power spectral density matrix, and the results are shown in Figure 6.
Figure 7(g~l) is the analysis of power spectrum and time-frequency on the separated signals. Figs g, h and i correspond to graphs j, k and l respectively.

Figure 7. (g~l) Split signal power spectrum and time-frequency diagram

According to Figure 7, the main frequencies of three separated signals are 90Hz, 60Hz and 140Hz respectively, which are the same as the main frequencies of vibration wave signals collected by sensors. The sensor mainly receives the body wave, so the separated signal can be considered as longitudinal wave (P wave) and shear wave (SH wave and SV wave). Since the frequency of longitudinal wave is higher than that of the shear wave, the separated signal 3 is the longitudinal wave and the separated signal 1 and 2 are the SH wave and SV wave formed by the shear wave through the interface.

6. Conclusion
In this paper, according to the actual situation of the sensor in collecting the vibration signals, a convolution-mixing model of two-channel single-signal is established. A frequency-domain convolution blind source separation algorithm based on the power spectral density matrix combined
diagonalization is used to separate the two-channel single vibration signal, and the separation effect is verified by the signal-to-interference ratio and the waveform similarity coefficient.

At the same time, the real vibration signal is dealt with by using a frequency domain convolution blind source separation algorithm based on power spectral density matrix and diagonalization to realize the separation of the vertical and horizontal wave of two-channel single vibration signal.

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