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Wavelet identification for the abnormal seismic wave component of rock burst

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Abstract: As we know, roof is composed of heterogeneous rock. When roof fractures, a large amount of energy would be released in the form of seismic wave. How to identify the abnormal signal of seismic wave is a much difficult problem, there are many methods used usually, such as Fourier Transformation, filter technique etc., but abnormal signal can't be recognized accurately. In this paper, multi-resolution wavelet technique is used to identify the first and second variation point, based on the Lipschitz α. A living example analysis shows, multi-resolution wavelet technique can identify the abnormal signal of seismic wave effectively in different scale, and the omen of roof fall can be grasped in order to forecast the roof fall accurately. It provides a new idea for the predication of catastrophe on rock mechanics and engineering.

1. Introduction

A large range of roof weighting will be induced after mining, accompanying a great amount of energy released in the form of elastic wave[1], and applying micro-seismic wave and acoustic emission techniques for monitoring rock fracture, roof weighting and rock burst have been concerned all over the world[4-7]. However, the shape of seismic wave caused by roof weighting etc., regarded as superposition of high-frequency and low-frequency signals, is so complex that abnormal information which indicating system catastrophe cannot be identified using traditional technique. Fortunately, the technique of wavelet analysis has been applied successfully in such fields as signal process[8], earthquake[9] and micro-cavity detection of composite materials[10] etc. In this paper, multi-resolution wavelet technique that is used to identify the first and second variation point of seismic wave caused by roof weighting is introduced.

2. Theory of Multi-resolution Wavelet Technique

Transformation Function of Discrete Wavelet

Wavelet analysis is a kind of method of time and frequency localization with fixed window area, but variable Takagi window shape, as well as the window changes with time and frequency. Wavelet transformation is of higher frequency resolution and lower time resolution in the part of low-frequency, and higher time resolution and lower frequency resolution in high-frequency part. This feature brings wavelet transformation self-adaptability during processing signal.

Assume $\psi(t) \in L^2(R)$. $L^2(R)$ is a square integrable real space that is considered as energy-limited signal space, Fourier transformation of $\psi(t)$ is $\hat{\psi}(\omega)$. When $\hat{\psi}(\omega)$ satisfies the following condition

$$C_\psi = \int_R \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty \tag{1}$$

Then $\psi(t)$ can be called basic wavelet. A wavelet series or wavelet base can be derived from the transformation of the function of $\psi(t)$ including scaling-down, scaling-up and shift transfer. As to continuous condition, the wavelet base is

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi \left| \frac{t-b}{a} \right| \quad a,b \in R; a \neq 0 \tag{2}$$

Where a is scaling factor , b is shift factor.
As to discrete condition, the wavelet series is

$$\psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j} t - k) \quad j,k \in Z \tag{3}$$

Multi-resolution Wavelet Analysis

If $\phi(x)$ is defined as scaling function, then one basic character is the following scale based on binary scale can be defined

$$\phi_2^j(x) = 2^j \phi(2^j . x) \tag{4}$$

Where j=0, -1, -2, …,. Orthogonal basis set of scaling function can be obtained by the following method: First, to expand the function $\phi(x)$ using the coefficient 2^j; then to shift the function $\phi(x)$ by $2^{-j}n$, and to make $\phi(x)$ normal using $\sqrt{2^{-j}}$.

$$\sqrt{2^{-j}}\phi_2^j(x - 2^{-j}n) \tag{5}$$

The wavelet function ψ in the formula (3) can be defined by the following form:

$$\psi_2^j(x) = 2^j \psi(2^j \cdot x) \tag{6}$$

Similarly, the orthogonal basis set of wavelet function can be obtained in such way: First, multiply the function $\psi(x)$ using the coefficient 2^j, then shift the function $\psi(x)$ $2^{-j}n$, and make $\psi(x)$ normal using $\sqrt{2^{-j}}$.

$$\sqrt{2^{-j}}\psi_2^j(x - 2^{-j}n) \tag{7}$$

Using Mallat algorithm[11], primary signal series can be decomposed into approaching signal and specific signal separately.

Approaching signal: When the resolution is equal to 2^j, the discrete approaching of the function f can be derived from convolution with the scaling function

$$C_2^j f = \langle f(x), \phi_2^j(x - 2^{-j}n)\rangle \tag{8}$$

Where <, > stands for inner product of both functions. Thus, the operator C_2^j produces an approaching signal pattern when the resolution is equal to 2^j, this just has the similar effect of low-filter.

Specific signal: When the scale of signal changes from 2^{j+1} to 2^j, there is a residual signal , which can be extracted from convolution of the function $f(x)$ and the transformation of scaling and shifting wavelet function, referred as specific signal when resolution is equal to 2^j ,

$$D_2^j f = \langle f(x), \psi_2^j(x - 2^{-j}n)\rangle \tag{9}$$

the operator D_2^j generates the detail part of signal continuously, which has the similar effect of band filter. So the concerned signal is decomposed to the approaching part C and detail part D.

3. Theory Of Wavelet Identification For Seismic Wave Catastrophe Due to Roof Weighting

Fourier transformation can only determine the macrocosm properties of the singularity of function, but it can difficultly determine the position and distribution of singularity in space. While wavelet transformation has the property of localization of space, so it is effective to analyze the position and magnitude of singularity of signal.

There are usually two kinds of circumstances about singularity of signal. First, the amplitude of signal changes suddenly at some moment, which leads to discontinuousness of signal, the catastrophe point of amplitude is defined as the first variation point; Secondly, signal seems to be smooth apparently, and the amplitude keeps steady, however the first order differentiation of signal produces catastrophe, discontinuous as well. It is defined as the second variation point. The local singulartity of function can be described by the Lipschitz index. Assume n is nonnegative integer, $n < a \leqslant n+1$. If there are two constants A, $h_0(>0)$, and $P_n(h)$ polynomial of degree n, satisfying the following formula as to any h ($\leqslant h_0$)

$$|f(x_0 + h) - P_n(h)| \le A|h|^a \tag{10}$$

then at the point x_0, $f(x)$ is called Lipschitz α. If the above formula satisfies all $x_0 \in (a,b)$, $x_0 + h \in (a,b)$ as well, then $f(x)$ is consistent Lipschitz α at the range of (a, b).

Obviously, Lipschitz α of $f(x)$ at point x_0 describes normal of the function at the point. The larger the index Lipschitz α is, the smoother the function is. If the function is continuous and differentiable at some point, then the index Lipschitz α is equal to 1. If the function is differentiable, but the derivative is bounded and discontinuous, then the index Lipschitz α is still equal to 1. If the index Lipschitz α is lower than 1 at the point x_0, then the function at the point is defined to be singular. If the function is discontinuous but bounded at point x_0, then the index Lipschitz α

of the point equals zero.

While analyzing the kind of local singularity using wavelet theory, the wavelet coefficient depends on the features of the function $f(x)$ in the neighborhood of the point x_0 and the scaling of wavelet transformation. Assume $f(x) \in L^2(R)$, $\forall x \in \delta x_0$, wavelet $\psi_{(x)}$ satisfies continuous and differential, and has n order die way moment (n is positive integer)

$$|Wf(s,x)| \le Ks^{a} \qquad (K \text{ is constant}) \tag{11}$$

then α is named singular index of x_0 point (or Lipschitz index).

Therefore, the catastrophic features of seismic wave can be identified by Lipschitz index.

4. Instance Analysis

Immediate roof of No. 5 seam of Mentougou Mine of Beijing Mining Bureau is high strength sandstone of 5 m thickness. Unilateral strength of compression is 110 MPa, brittleness is intense, and roof will fall soon once it fracture. The following will make the first and second catastrophe analysis on seismic wave caused by roof fracture and fall.

The First Catastrophe Analysis

The original signal is decomposed on the sixth layer. If a6 is the low-frequency part of the sixth layer, and d1, d2, d3, d4, d5, d6 are the high-frequency parts from the first to the sixth layer. Fig. 1 illustrates that the original signal, low-frequency and high-frequency signal all show abnormality at the first catastrophe range with t=125s~215s, with which corresponding from initial damage to fracture of roof. However, on the eve of noticeable movement of roof, the original signal, low-frequency signal a6 and high-frequency signal d4, d5, d6 are all normal. When t=385s~410s, high-frequency signals d1, d2, d3 start to be abnormal, and the roof fall when t=440s.

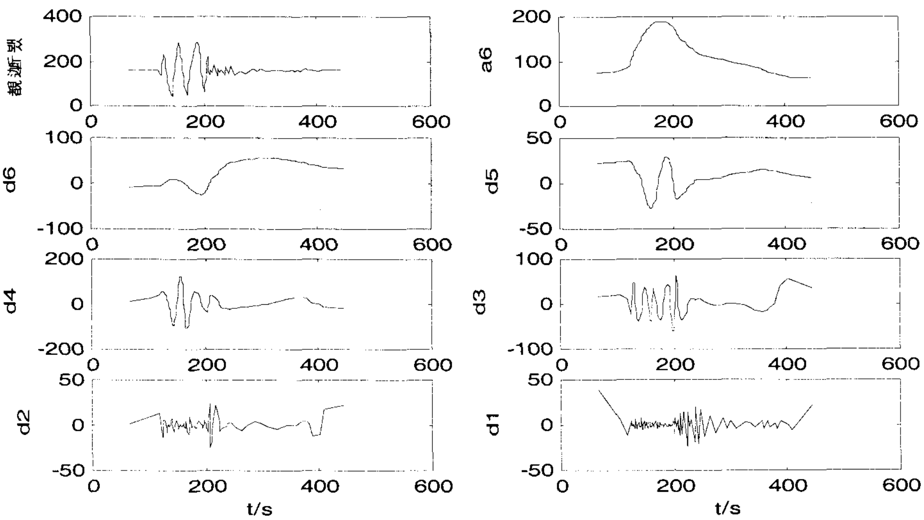

Fig. 1. The first catastrophe analysis.

The Second Catastrophe Analysis

As Fig.2 shows, the original signal is differential and decomposed on the second layer. If a2 is the low-frequency part of the second layer, d1, d2 are high-frequency parts of the first and the second layers. The figure illustrates the original signal, low-frequency part a2 and high-frequency part d2 all show abnormality when t=125s~215s, while d1 shows to be abnormal when t=125s~250s. The d1 is 35s longer than that of the origin signal, low-frequency signal and high-frequency signal.

Comparing the two methods of catastrophe identification, we can conclude that the first catastrophe identification is more feasible on seismic wave analysis due to roof weighting.

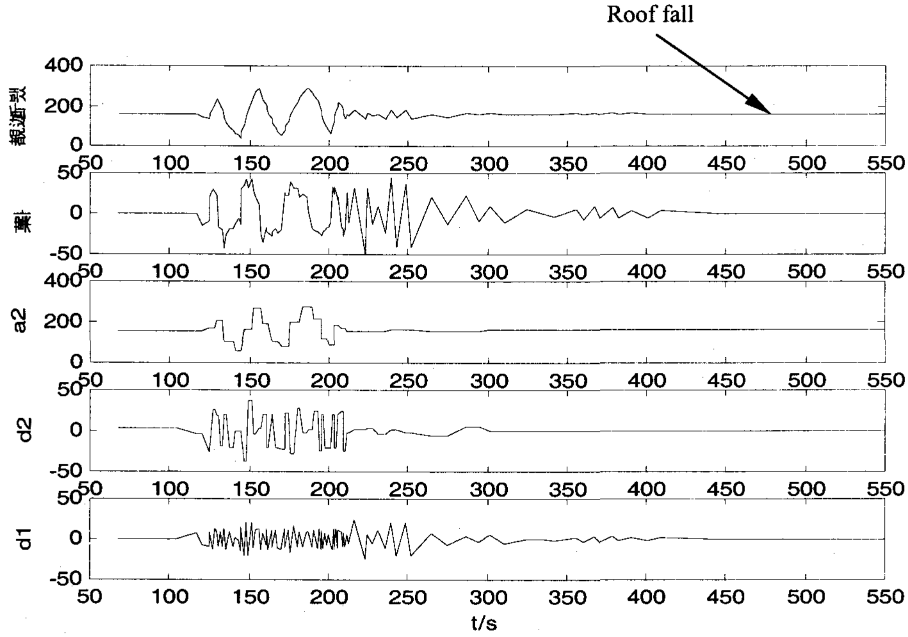

Fig. 2. The second catastrophe analysis.

5. Conclusions

Roof is a kind of typical heterogeneous material. The fracture of roof will release a large amount of energy and result in seismic wave. Multi-resolution wavelet technique can be used to effectively analyze the catastrophe of seismic wave in different scale and to grasp the information of roof fall. The paper provides a new idea for the prediction analysis of catastrophe on rock mechanics and engineering.

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