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Suppressing non-stationary random noise in microseismic data by using ensemble empirical mode decomposition and permutation entropy

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ABSTRACT

Microseismic signal is inevitably mixed with non-stationary random noise in the process of acquisition, which is difficult to be separated from non-stationary random noise by using the traditional methods of linear filtering and spectrum analysis. Thus a suppressing method of non-stationary random noise is proposed. It firstly conducts the multi-scale decomposition of microseismic signal containing noises based on ensemble empirical mode decomposition (EEMD). Several components of Intrinsic Mode Functions (IMFs) are obtained and they are arranged in descending order according to their frequencies. In order to accurately identify the signals and noises in these IMF components and compare the normal microseismic signals with noises, the quantity of permutation entropy is introduced to describe the characteristics of normal microseismic signal. The threshold value of permutation entropy is used to extract the IMF components conforming to the characteristics of microseismic signal. These IMF components are reconstructed to suppress the noise. Through simulation and the test for the practical microseismic monitoring data, it is indicated that the method has a better treatment effect for non-stationary random noise in microseismic signal.

1. Introduction

Microseismic monitoring technology has been widely used in mine disaster monitoring, oilfield fracturing and other engineering fields, due to its own technical limitations of seismic geophone and external monitoring of environmental impact, the microseismic data collected in actual are inevitably mixed with noise, such as electromagnetic interference, background noise, mechanical vibration, blasting shock. These noises are nonlinear, non-stationary and random, sometimes they even make the actual occurrence of microseismic signal distortion and cover the real process of rock fracture propagation, affecting source location, focal mechanism explanation and other subsequent work. Since the frequency bands of microseismic signal and external random noise are totally or partly overlapped, it is difficult to separate microseismic signal from non-stationary random noise by using the traditional methods of linear filtering and spectrum analysis. Thus a proper suppressing method of non-stationary random noise should be proposed.

To suppress the noise and retain effective microseismic signal have been a hot issue of research scholars at home and abroad, the current method of suppressing non-stationary random noise in the microseismic signal are: wavelet threshold method (Gaci, 2014; Beenamol et al., 2012; Kopsinis and McLaughlin, 2009), time-frequency peak filtering method (Tian and Li, 2014; Lin et al., 2015), singular spectrum analysis de-noising method (Oropeza and Sacchi, 2011), empirical mode decomposition method (Li et al., 2013; Zheng et al., 2014; Jia et al., 2015), the pressing performance of above-mentioned methods to the non-stationary random noise of earthquake monitoring data has better effects. Among them, the wavelet threshold method has the advantages of simplicity, less calculated amount and so on. Currently, however, there is no determination method for the selection of wavelet basis and decomposition level. Moreover, the recovery of raw signal depends on the selection of wavelet threshold value. If the threshold value is too large, part of the effective signal will be lost; if it is too small, overmuch noise will be retained, causing the difficulty of application and promotion. Time-frequency peak filtering method has taken effect on recovering the seismic exploration data of low signal-to-noise ratio, however, the premise of the method's unbiased estimation is supposing the signal is linear

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and the noise is Gaussian white noise. Actual seismic exploration data is mostly nonlinear and the noise has the character of impulse, thus the unbiased estimation criteria of time-frequency peak filtering have not been met. Although by adding time window, which accords with Wigner-Ville Distribution, the local linearity could be increased, it is difficult for single window length to keep balance between signal recovery and noise suppression. If the selected window length is too small, then the signal linearity will be increased with little effect of noise suppression; if it is too large, the noise suppression is effective with serious loss of signal. Singular spectrum analysis de-noising takes comparatively more prominent de-noising effect on signal of smaller time domain waveform fluctuation. However, for the signal of larger time domain waveform fluctuation, suitable noise platform parameter should be selected to de-noise effectively. But currently, there is no clear definition of the selection rules of noise platform parameter. Empirical mode decomposition (EMD) method is known as a major breakthrough in traditional time-frequency analysis methods such as Fourier transform and wavelet transform (Huang et al., 1998). EMD method has shown unique advantage in non-stationary signal processing field, and has already been widely used in the fields of mechanical fault diagnosis, picture processing, earthquake signal analysis and inversion (Li et al., 2015; Linderhed, 2011; Tong et al., 2013), etc. The method, on the premise of having no need for signal prior knowledge, is able to adaptively decompose into a series of Intrinsic Mode Function (IMF), which is arranged in a descending order by frequency for input signal according to the characteristics of the signal. Theoretically, in signal de-noising processing field, the de-noising signal can be obtained if only IMF is reconstructed after finding out the bound between signal and noise. However, the original method, defining the dividing point between signal and noise based on energy criterion, has the disadvantage of low stability. The IMF, taken after EMD decomposition, has mode mixing problem. Thus the popularization and application of EMD in signal de-noising field is greatly limited.

Aiming at the existing problems of EMD de-noising method mentioned above, a method of suppressing non-stationary random noise in microseismic signal through ensemble empirical mode decomposition (EEMD) and permutation entropy (PE) is proposed. EEMD is able to balance the signals by adding Gaussian white noise into the pending signal and obtain the average components of IMF after the EMD decomposition for several times. This method has effectively solved the mode mixing problem existing in traditional EMD method (Wu and Huang, 2004, 2009; Flandrin et al., 2004); in order to accurately identify the bound between the signals and noises in IMF components and compare the normal microseismic signals with noises, the dissertation introduces the permutation entropy to describe the characteristics of normal microseismic signal. Furthermore, the threshold value of permutation entropy is used to distinguish IMF components conforming to the characteristics of microseismic signal. These IMF components are reconstructed in order to suppress the non-stationary random noise in microseismic signal.

2. Related theoretical basis

2.1. Ensemble empirical mode decomposition (EEMD)

Although a large number of application examples show that the result of EMD decomposition is reasonable and effective, until now there is no complete mathematical foundation of EMD algorithm, of which the convergence, uniqueness and orthogonality in the decomposition progress have not been rigorously proved mathematically (Sekine, 2008). Therefore EEMD algorithm parameters still depend on the experience and attempt. The research shows that when signals consist of pulse signals or intermittence signals, decomposing signals by EMD causes mode mixing easily (Wu and Huang, 2004; Flandrin et al., 2004). Wu et al. come up with the EEMD method with the improvement of mode mixing through the research on statistical characteristics of white noise signals. The basic steps are as follows:

Step 1: Suppose $x(n)$ is original signal timing sequence, n is sampling point number, and add Gaussian white noise into $x(n)$.

$$x'(n) = x(n) + b(n), \tag{1}$$

where $b(n)$ represents Gaussian white noise;

Step 2: Decompose $x'(n)$ with EMD, and then get some IMF sequence, of which the number is represented by k.

$$x'(n) = \sum_{i=1}^{k} imf_i(n) + r(n) \tag{2}$$

Step 3: Repeat step 1 and 2 for N times, and add different Gaussian white noise into original signal for each time, then get:

$$x'_j(n) = \sum_{i=1}^{k} imf_{ji}(n) + r_j(n), j = 1, 2, \ldots, N \tag{3}$$

Step 4: According to spectrum zero mean theory of Gaussian white noise, add IMF after decomposition and then average the sum, and then k IMF corresponding to the original signal can be expressed as follows:

$$imf_i(n) = \frac{1}{N}\sum_{j=1}^{N} imf_{ji}(n), i = 1, 2, \ldots, k \tag{4}$$

Step 5: The original signal can be decomposed as follows:

$$x(n) = \sum_{i=1}^{k} imf_i(n) + r_i(n) \tag{5}$$

In fact, the main reason of mode mixing is that the choice of extreme points is certainly affected when signals consist of pulse noises or intermittence noises causing distribution asymmetry of extreme points, thus the obtained envelope is the combination of the partial envelope and the signal envelope of noises. Pulse noises or intermittency noises of signals to be corrected by adding white noises for several times in order to improve extreme point distribution of signals and to control mode mixing effectively.

Two important parameters to be determined for the EEMD algorithm are: added white noise amplitude and times to add white noise. If added white noise amplitude is smaller than the amplitude of the original signal, the added Gaussian white noise cannot influence the choice of pole, and mode mixing problem cannot be effectively addressed; if added white noise amplitude is bigger, then false harmonic components will be incorporated into the IMF and make a signal error. According to the proposal of Wu and Huang, 2004, in this article, added white noise amplitude is set to 0.2 times the original signal amplitude, and N representing the times of adding Gaussian white noise in EEMD obeys statistical rule of (6) (Zhu et al., 2013):

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{N}} \tag{6}$$

Among them, ε stands for Gaussian white noise amplitude, ε_n for the error between signal from the accumulation of original signal and decomposition of EEMD, that is to say, once Gaussian white noise amplitude is determined, To original signal, the more Gaussian white noise we add, the closer the result will be. Generally, if $\varepsilon_n = 0.02$, then $N = 100$.