Research Article

Application of Low-Frequency Processing Method Based on VMD Algorithm in Blasting Signal Processing

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In the field of blasting vibration signal analysis, accurate removal of low-frequency noise in the signal has important practical significance. In view of the shortcomings of the existing methods, such as cumbersome calculation and limited scope of application, a method based on variational mode decomposition (VMD) to remove low-frequency noise was proposed. In this paper, the parameter selection of VMD algorithm to identify low-frequency noise of blasting signal is optimized by simulation experiment. The results show that frequency has little influence on the decomposition effect. When the frequency of low-frequency noise is between 0 and 5 Hz, the influence of frequency on the decomposition effect remains basically unchanged. The amplitude has a significant effect on the decomposition effect. The smaller the amplitude, the worse the decomposition effect of the VMD method. Taking the excavation of the Badaling Great Wall Station as the background, the LSM method, EMD method, and VMD method are used to remove the low-frequency noise of the randomly selected test signals in order. Compared with the LSM method and the EMD method, the signal processed by the VMD method does not have modal mixing and does not have much low-frequency noise residue. It has more extensive applicability in removing low-frequency noise of blasting signal.

1. Introduction

Drilling and blasting is an indispensable construction method for tunnel excavation. When a detonation occurs, part of the explosive energy directly breaks the target rock, and the remaining energy generates a considerable impact load in the surrounding rock. The remaining energy can create several undesirable environment effects such as vibration, flying stones, shock waves, and back break. Out of the fore mentioned effects, ground vibration is the most harmful to the surrounding environment and is considered to be the primary hazard in the explosion process [1–5].

During the acquisition of blasting vibration, changes in the surrounding environment and unstable sensor performance may cause the vibration waveform to deviate from the center of the baseline. The components of blasting signal with slow change, small period, and low frequency are called the signal trend term, also known as low-frequency noise. In general, the main frequency of blasting vibration is above 20 Hz, and the sensor can only accurately measure the vibration above 5 Hz. Therefore, it is generally considered that the part of the data with a frequency less than 5 Hz is low-frequency noise. The low-frequency noise changes the time-domain analysis and spectrum analysis of the signal, and even distorts the low-frequency spectrum in its entirety. Therefore, accurately removing the low-frequency noise of the signal has important practical significance for improving the accuracy of blasting vibration signal analysis [6].

The least squares baseline correction method, proposed by Berg and Housner, is to minimize the sum of squared residuals between the observed value and the fitted value [7]. At the same time, researchers have proposed the removing average of pre-event (RAP) method, which eliminates the average of fluctuations before the start of recording to achieve the purpose of correcting the baseline. However, it does not attempt to correct
baseline changes that are subsequent to the onset of shaking [8–11].

In the early 21st century, wavelet packets and EMD were widely used in the field of blast signal baseline calibration. As a common processing method of blasting vibration signals, wavelet packet through selecting suitable wavelet base function and the layer number of decomposition of the original signal decomposition, and then choosing the appropriate threshold function to quantify the wavelet decomposition coefficients, to find and eliminate the trend item of the corresponding coefficient after wavelet decomposition, the wavelet coefficient of refactoring is completed the baseline calibration. EMD is a series of intrinsic mode function (IMF) components with different characteristic time scales by adaptive decomposition based on the local features of the analyzed signals. In general, the low-frequency noise is at a different scale from the normal blasting signal, so the EMD algorithm can quickly remove it.

But both methods have flaws: the wavelet package needs to determine the wavelet basis function and the decomposition order in advance, and improper basis functions can lead to a decrease in the accuracy of signal reconstruction [12–15]. There is no scientific theoretical basis for the end criterion of the EMD method through envelope decomposition. It may cause modal aliasing of IMF components, which will cause the IMF components to lose meaning [16, 17].

With the development of the research, many new methods of low-frequency noise removal have been proposed. Zhang et al. [14] used adaptive wavelet to remove the low-frequency noise of the blasting signal and achieved good results; Ling et al. [15] constructed a biothogonal wavelet base, which has been proved by experiments to have good applicability in the blasting signal processing. Based on EEMD, Han et al. [8] proposed a low-frequency noise processing method for blasting signals in the near area of deep-hole step blasting. Similar research methods have been proposed based on wavelet packets and EMD algorithms. Although this has helped make up for some of the defects of the two methods, it still has some problems such as time consuming and lack of theoretical basis. There is no universal model that can be blindly applied.

In 2014, Dragomiretskiy and Zosso [18] proposed variational mode decomposition (VMD) based on wiener filtering and variation problem construction. In this method, the frequency center and bandwidth of each component are determined by iteratively searching the optimal solution of the variational model so that the frequency domain subdivision and the effective separation of each component can be realized adaptively. This makes the VMD algorithm have a strong low-frequency pickup ability, and the problem of modal aliasing of IMF components will not occur. In recent years, the VMD algorithm has been widely used in noise processing of mechanical signals, and it is believed that the VMD algorithm has unique advantages in dealing with random signals.

Qi et al. [19] used a whale optimization (WOA) algorithm to search globally the number of parameter combination decomposition $K$ and the quadratic penalty factor $\alpha$ in the variational modal decomposition (VMD) algorithm, and determined the optimal combination $(K, \alpha)$ according to the search results. Gu and Zhou [20] used a matrix bundle method to solve optimal decomposition parameters. Zheng et al. [21] used grasshopper optimization algorithm (GOA), which took correlation kurtosis as fitness function, to select the parameters of variational mode decomposition adaptively.

Reference [22] constructed a decomposition signal containing low and high frequencies, and analyzed the decomposition effect of the VMD algorithm on the constructed signal through simulation experiments, and proved that the VMD algorithm has a strong ability to recognize low-frequency component signals.

In this paper, the VMD algorithm will be used in the field of removing low-frequency noise from blasting signals. In order to solve the problem of parameter selection of the VMD algorithm, based on the feature that the trend term of blasting signal is a low-frequency signal, The signal simulation is carried out by using MATLAB program, and the value of $K$ and $\alpha$ is studied to achieve the purpose of rapid and accurate application of the VMD algorithm in engineering, and its application in practical engineering is verified. In the Section 2, the principle of VMD is introduced, and in the Section 3, VMD parameters are determined by the low-frequency characteristics of blasting signal, and the process of removing low-frequency noise is summarized. In Section 4, the application range of the VMD algorithm is obtained by signal simulation. Finally, the method is applied in practical engineering, and the results of LSM and EMD are compared to prove its application value.

2. Variational Mode Decomposition Principle

The VMD algorithm decomposes the signal into multiple IMF (intrinsic mode functions), and the IMF component is defined as a signal as follows:

$$u_k(t) = A_k(t)\cos(\phi_k(t)),$$

(1)

where $u_k(t)$ is each IMF component; $A_k(t)$ is the instantaneous amplitude, $A_k(t) \geq 0$; $\phi_k(t)$ is the instantaneous phase, $\phi_k(t) \geq 0$.

The EMD algorithm uses the cyclic screening and stripping method to obtain the IMF component. Defects such as modal aliasing often occur during the decomposition of nonstationary random signals. Different from the EMD algorithm, the VMD algorithm redefines the IMF component on a sufficiently long interval $[t - \delta, t + \delta]$, $\delta = 2\pi/\phi_k(t)$; the mode $u_k(t)$ can be considered to be a pure harmonic signal with amplitude $A_k(t)$ and instantaneous frequency $\phi_k(t)$. The immediate consequence of the newer IMF definition is limited bandwidth. This is the reason why it can solve the mode aliasing problem.

2.1. Construction of Variational Problems. We assume that each modal component is tightly distributed around a center frequency and has a limited bandwidth. The center
frequency will change as the decomposition changes. The core of the variation problem is to find the sum of the estimated bandwidth of the smallest IMF component on the premise that the input signal \( f(t) \) is equal to the sum of IMF components, and the construction process is as follows:

1. For each IMF component \( u_k(t) \), after the analytical signal is constructed using the Hilbert transform, the respective estimated center frequencies are tuned by mixing the exponents to modulate the spectrum of each IMF component to the corresponding base band:

\[
\left[ (\delta(t) + \frac{j}{\pi t}) u_k(t) \right] e^{-j\omega_{t_k}},
\]

where \( u_k = \{ u_1, \ldots, u_k \} \) represents the IMF components obtained by decomposition; \( \omega_k = \{ \omega_1, \ldots, \omega_k \} \) is the center frequency of each IMF component; \( \delta(t) \) represents the Dirac function.

(2) We estimate the bandwidth of each IMF component based on the Gaussian smoothness of the demodulated signal.

\[
\begin{align*}
\min_{\{u_k\}, \{\omega_k\}, \lambda} \bigg\{ & \sum_{k=1}^{K} \left\{ \partial_t \left[ (\delta(t) + \frac{j}{\pi t}) u_k(t) \right] e^{-j\omega_{t_k}} \right\} \\
& \text{s.t. } \sum_{k=1}^{K} u_k(t) = f(t) \bigg\}
\end{align*}
\]

2.2. Solving Variational Problems. In order to solve the constraint variation problem in equation (3), the penalty factor \( \alpha \) and Lagrange multiplication operator \( \lambda(t) \) are introduced. The penalty factor \( \alpha \) is a large positive number and the accuracy of signal reconstruction is guaranteed in the presence of Gaussian noise. The role of \( \lambda(t) \) is to maintain strict conditions. The extended Lagrange expressions constructed by them are as follows:

③ For all \( W > 0 \) components, update \( u_k, \omega_k \)

The update and solution process of \( u_k^{n+1} \) is as follows: First calculate equation (5) in the frequency domain to get the frequency domain function corresponding to \( u_k^{n+1} \). Then, the inverse Fourier transform of equation (5) is carried out to obtain the IMF component in the time domain.

3. A Low-Frequency Noise Elimination Method Based on VMD

3.1. Parameter Selection of VMD Algorithm. The same as many classic segmentation algorithms, the VMD algorithm is needed to tell in advance how many clusters (or modes, in the present case) or data are to be binned. The value of the number of decomposition layers \( K \) directly affects the decomposition results. At the present, the research on the variable \( K \) in the VMD decomposition is still in its infancy, and there is no unified solution method [23–28]. In view of
this problem, the value of $K$ in the VMD method will be studied in the following section.

The blasting vibration signal is a random nonstationary signal, which can be regarded as generated by the superposition of IMF components with a number of $N$. Because the frequency of the blasting signal is widely distributed and irregular, its $N$ value is large. When $K = N$ is taken, the VMD algorithm cannot be calculated due to more layers, so the VMD algorithm is usually underdecomposed when it decomposes the blast signal. At this time, some modes will be shared or even discarded by neighboring modes (depending on the number of $\alpha$).

The first-order IMF component in the VMD algorithm is always the lowest frequency component of the signal. Its bandwidth changes with parameter changes, but the change starts from the end with the higher frequency, as shown in Figure 1. Therefore, the low-frequency portion of the first-order IMF component does not change with $K$. The frequency $\omega_{r(t)}$ of low-frequency noise $r(t)$ is less than $\omega_k$ and is the low-frequency part of IMF component of order 1. Therefore, in general, the value of $K$ does not affect the low-frequency noise. In order to save calculation time, the parameter $K$ is set to 2.

At this time, the first-order IMF component contains low-frequency noise and other modal information. The next step is to set a reasonable second penalty factor $\alpha$ and extract low-frequency noise as a complete first-order IMF component. The value of $\alpha$ will affect the decomposition accuracy. The lower the value, the larger the bandwidth of each IMF component. The higher the value, the smaller the bandwidth of each IMF component. And as the value of $\alpha$ increases, the calculation time will increase accordingly, and the program will enter an endless loop [11, 12].

In order to obtain a reasonable value of $\alpha$, five different low-frequency noises are added to the measured signal in Figure 2, respectively. The root-mean-square error of low-frequency noise with different values and the computation time are also plotted, as shown in Figure 3. It can be seen from Figure 3(a) that the RMSE value decreases with the increase of $\alpha$, and the rate of decrease also accelerates. However, it is basically unchanged after $\alpha$ value reaches 5000. The calculation time in Figure 3(b) is proportional to $\alpha$. When $\alpha$ reaches a certain “node,” increasing the value of $\alpha$ will only increase the computing time, and will not increase the decomposition effect significantly. After a large amount of data verification, the signal length of 2.5 times is selected as the value of this node. Of course, the value of $\alpha$ can be appropriately increased with the requirements of the decomposition effect.

3.2. Low-Frequency Noise Removal Method of Blasting Signals Based on VMD. Based on the characteristics of blasting vibration signals, this paper proposes a method for identifying differential delay time based on variational mode decomposition—VMD identification method. This method can accurately extract the low-frequency noise of the signal and avoid signal distortion caused by excessive elimination [29–39]. The detailed steps are as follows:

1. According to the length $L$ of the blasting vibration signal, the input parameter $\alpha = 2.5L$; the number of decomposition layers $K$ is fixed at 2.

2. The first-order IMF component is extracted, and this component is the low-frequency noise of the signal.

3. By removing low-frequency noise from the original signal, a corresponding trendless signal can be obtained.

4. VMD Law Application Conditions

In order to verify the applicable conditions and effectiveness of the VMD method proposed in this paper, a simulation experiment was performed using the trendless vibration signal $v(t)$.

\[
s(t) = v(t) + n(t),
\]

\[
n(t) = a \cos(2\pi f_1 t) + \sin(2\pi f_2 t),
\]

where $s(t)$ is the combined blasting vibration signal containing low-frequency noise; $n(t)$ is the added low-frequency noise.

Taking the original non-trend blasting signal in Figure 4(a) as an example, the low-frequency noise shown in Figure 4(b) is added to the original signal, and the mixed signal is VMD decomposed. The results are shown in Figures 4(d)–4(f). In order to study the applicable conditions of the VMD method, the decomposition effect (DE) is defined as shown in the equation as follows [14]:

\[
DE = \frac{\sum_{t=0}^{T} |x_i(t) - \text{IMF}_i(t)|}{\sum_{t=0}^{T} |x_i(t)|}
\]

where $DE$ is the index of decomposition effect; $T$ is the signal length.

After a large number of experiments, it was found that the larger decomposition index $DE$ had larger the difference between the decomposition result and the original signal. The closer $DE$ is to 0, the smaller the difference between the decomposition result and the original signal, and the better the decomposition effect when $DE < 0.1$. This means that the VMD method successfully extracted the low-frequency noise of this mixed signal.

In order to obtain the applicable conditions of the VMD decomposition method, the decomposition index distribution map of the VMD decomposition method under different parameters is obtained by changing the frequency and amplitude of the added low-frequency noise. In order to eliminate the influence of other factors, the original blasting signal is denoised and normalized. The amplitude of the added low-frequency noise is between 0 and 1 time than that of the maximum amplitude of the original signal. The frequency range is between 0 and 5 Hz. The signals in Figures 2 and 4(a) are used as the original signals 1 and 2, respectively, and the processing results are shown in Figures 5 and 6, respectively. When $DE$ is 0.1 in Figures 5(a)–5(d), the low-frequency noise amplitudes are 0.2, 0.21, 0.11, and 0.12, respectively. The frequency has little effect on $DE$ within 0–5 Hz. The distribution
Figure 1: Continued.
Figure 1: VMD decomposition results under different parameters. (a) $\alpha = 1000$ with (i) $K = 2$, (ii) $K = 3$, (iii) $K = 4$, and (iv) $K = 5$. (b) $\alpha = 500$ with (i) $K = 2$, (ii) $K = 3$, (iii) $K = 4$, and (iv) $K = 5$.

Figure 2: Continued.
maps of the DE of Figures 5(a) and 5(b) are basically the same, indicating that the complexity of low-frequency noise has a small effect on the effect of the VMD decomposition method. The amplitude of the maximum component of the trend term in Figure 5(a) is twice that of Figure 5(c), while the amplitude of other trend terms remains unchanged, and the distribution of DE is also two times different. Therefore, it is considered that the maximum amplitude of the trend term plays an important role in VMD decomposition. The amplitude exchange results of the two functions are shown in Figures 5(c) and 5(d). It is found that the DE produces some transformation, but the transformation is not obvious.

In summary, the VMD decomposition method has different decomposition effects on different low-frequency noises, and the frequency and amplitude of low-frequency noise will affect the VMD decomposition index. Among them, the frequency has a small impact on the decomposition index. When the low-frequency noise frequency is between 0 and 5 Hz, the influence of the frequency on the decomposition index is basically unchanged. The amplitude has a significant effect on the decomposition index. And the smaller the amplitude, the worse the decomposition effect of the VMD method.

The result of signal 2 is shown in Figure 6; its low-frequency noise parameters are exactly the same as those in Figure 3. It can be found that by comparing the distribution of decomposition index, the effect of the frequency and amplitude of the low-frequency noise on the decomposition index is the same as the result of signal 1. The effect of frequency on the decomposition effect is small, and the effect of amplitude is significant. It can be seen that the VMD decomposition method will eliminate the low-frequency noise of the signal.

5. Practical Applications

5.1. Method for Low-Frequency Processing in Blasting

5.1.1. Principle of Low-Frequency Processing in EMD algorithm. Hilbert Huang transform (HHT) is an important technique for nonstationary signal analysis. The main idea of the empirical mode decomposition (EMD) algorithm is to decompose the signal to be analyzed into a series of IMF.

Assuming that the vibration test signal to be analyzed is $S(t)$, IMF component is $S_i(t)$ and residual component is $R(t)$, the following results can be obtained through decomposition:

$$S(t) = \sum_{i=1}^{n} S_i(t) + R_n(t),$$

where $n \in Z^+$ represents the order of EMD decomposition.

The convergence of EMD decomposition makes the residual signal component $R_n(t)$ obtained by decomposition a monotonic function, which contains the component with the lowest frequency in the test signal, and its period is...
Figure 3: The processing results of different low-frequency noises. (a) RMSE. (b) Running time.

Figure 4: No trend blasting vibration signal. (a) Original signal. (b) Trend. (c) Mixed signal. (d) Decomposing the signal. (e) Trend term after decompose. (f) Error.
Figure 5: The decomposition effect of signal 1 under different parameters. (a) $A \sin(2\pi ft) + 0.25A \cos(4\pi ft)$. (b) $A \sin(2\pi ft) + 0.25A \cos(4\pi ft) + 0.5A \sin(\pi ft)$. (c) $0.5A \sin(2\pi ft) + 0.25A \cos(4\pi ft)$. (d) $0.25A \sin(2\pi ft) + 0.5A \cos(4\pi ft)$.

Figure 6: Continued.
greater than the length of the sampling signal, so $R_n(t)$ is the trend term contained in the test signal.

5.1.2. Principle of Low-Frequency Processing by Least Square Method. It is assumed that the sampling sequence of the measured blasting vibration signal is $\{S_k\}$ ($k = 1, 2, 3, \ldots, n$), sampling interval $\Delta T = 1$ for simplification, and we assume that a polynomial function $\bar{S}_k$ can be used to approximate sampling sequence $\{S_k\}$:

$$\bar{S}_k = a_0 + a_1k + a_2k^2 + \cdots + a_mk^m = \sum_{j=0}^{m} a_j k^j.$$  \hspace{1cm} (13)

The coefficient $a_j$ ($j = 1, 2, 3, \ldots, m$) needs to be determined to minimize the error square and $E$ between the approximation function $\bar{S}_k$ and the sampling data $S_k$:

$$E = \sum_{k=1}^{n} (\bar{S}_k - S_k)^2 = \sum_{k=1}^{n} (a_0 + a_1 k + a_2 k^2 + \cdots + a_m k^m - S_k)^2.$$  \hspace{1cm} (14)

The partial derivative of $E$ with respect to $a_j$ is zero, and a system of linear equations $m + 1$ can be generated as follows:

$$\sum_{k=1}^{n} \sum_{j=0}^{m} a_j k^{j+1} - \sum_{k=1}^{n} S_k k^i, \quad i = 0, 1, \ldots, m.$$  \hspace{1cm} (15)

By solving equation (10), $m + 1$ undetermined coefficient $a_j$ can be obtained, where $m$ is the order of the polynomial, $j \in [0, m]$. Then, the calculation formula of trend elimination can be obtained as follows:

$$\bar{S} = S_k - \bar{S}_k.$$  \hspace{1cm} (16)

5.2. Engineering Background and Testing. The Badaling Great Wall Station is located in the new Badaling tunnel under the Badaling Guntiangou parking lot, as shown in Figure 7. It was the first deep buried high-speed railway underground station in China to be constructed by the mining tunneling method. The length of the main body of the station is 450 m, and the buried depth of the line at the center is about 102.55 m. It is divided into three-arch sections and three-hole separation standard sections. The three-hole separation section is 398 m. The three-hole separation section is divided by the reserved rock mass. The minimum thickness of the rock mass is 2.23 m and the maximum thickness is 6 m. The blasting vibration needed to be strictly controlled. Therefore, the accuracy of the measured vibration velocity was required to be higher.

The blasting vibration signals monitored in the three-hole separation section often contain low-frequency noise. For the randomly selected test signals, trend term removal was performed by LSM, EMD, and VMD in turn [40], and the results are shown in Figure 8. The processing results of LSM are not ideal. The three signal processing results all contain significant low-frequency noise. Even in Figure 8(b), the signal starts and deviates from the baseline. The main reason is that LSM is mostly suitable for polynomial linear fitting, but blasting vibration belongs to the nonlinear random signal. The EMD method removes several inherent modal functions from the original signal to eliminate low-frequency noise. However, the decomposition process has
Figure 8: Continued.
Figure 8: Continued.
Figure 8: Continued.
disadvantages such as modal mixing, which causes arcs to appear at the signal baseline. In contrast, the VMD algorithm results are satisfactory, and the decomposed signal baseline is stable and meets engineering requirements. Therefore, the baseline calibration method based on the VMD algorithm has important significance in engineering blast vibration measurement.

6. Conclusion

In view of the advantage of variational mode decomposition in low-frequency recognition, this paper analyzed the parameter selection and application range of the VMD algorithm in detail. Taking the excavation of Badaling Great Wall station as the background, the treatment results of the LSM method, EMD method, and VMD method were compared and analyzed, and the following conclusions were obtained:

1) The principle of the VMD algorithm determines its advantages in low-frequency noise identification. Generally, the value of $K$ does not affect low-frequency noise. To save calculation time, the parameter $k$ is set to 2; when $\alpha$ reaches a certain “node,” increasing the value of $\alpha$ will only increase the computation time, and will not increase the decomposition effect significantly. After data verification, 2.5 times the signal length is selected as the value of this node.

2) The VMD method has different decomposition effects for different low-frequency noises, and the frequency and amplitude of the trend terms will affect the VMD method decomposition effect. Among them, frequency has little influence on the decomposition effect. When the frequency of low-frequency noise is between 0 and 5 Hz, the influence of frequency on the decomposition effect remains basically unchanged. The amplitude has a significant effect on the decomposition effect. The smaller the amplitude, the worse the decomposition effect of the VMD method.

3) The VMD method can accurately extract the low-frequency noise of the signal when eliminating the low-frequency noise of the signal, and has the ability to calibrate the baseline of the blasting signal. Compared with the LSM method and the EMD method, the signal processed by the VMD method does not have modal mixing and does not have much low-frequency noise residue. Instead, it has more extensive applicability in removing low-frequency noise of blasting signal.

This paper only uses the original VMD algorithm to process the low-frequency trend term of blasting signal. Because of the low-frequency characteristics of the trend term, there is no in-depth discussion on the selection of VMD parameters $K$ and $\alpha$. Although the parameter selection given in this paper can satisfy the removal of most blasting trend terms, this method will inevitably affect the accuracy of the results. Therefore, the future work can focus on improving the accuracy of the processing results and further expand the application scope of the VMD algorithm.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.
Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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