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A De-Noising Method for Track State Detection Signal Based on the Statistical Characteristic of Noise

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Abstract

Based on the statistical characteristics analysis of random noise power and autocorrelation function, this paper proposes a de-noising method for track state detection signal by using Empirical Mode Decomposition (EMD). This method is used to noise reduction refactoring for the first Intrinsic Mode Function (IMF) component in accordance with the "random sort-accumulation-average-refactoring" order. Signal autocorrelation function characteristics are used to determine the cut-off point of the dominant mode. This method was applied to test signals and the actual inertial unit signals; the experimental results show that the method can effectively remove the noise and better meet the precision requirement.

Keywords

Track Inspection, Long Wave Irregularity, Empirical Mode Decomposition, De-Noising

1. Introduction

Tracks are the infrastructure to train safe operation due to the uneven elasticity of track structure and rail base can cause rail line long wave irregularities [1] [2]. Inertia method is the main technical route in track detection [3]-[6]. Using strapdown inertial technology test track long-wave rough chronological, due to the inertia unit acceleration signal collected contain more low frequency noise, easy to cause integrator saturation, so we must do de-noising processing first before the integral on acceleration signal.

The complex signal can be decomposed into level signals step by step (*i.e.*, to smooth the signal processing) based on the empirical mode decomposition according to different time scales and get a series of intrinsic mode function characteristics of different scales. Each IMF component contains a signal from low frequency to high

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frequency of different ingredients and each frequency component that is included in the frequency changes over the signal itself [7] [8]. So the EMD can be thought of as a space-time filtering process based on signal extremum characteristic scale. This property is used in signal filtering analysis and noise reduction processing. In this paper, through the statistical characteristics analysis of random noise power and autocorrelation function, we put forward the EMD de-noising method based on noise statistical characteristics. Experimental results show that the method can effectively suppress noise and improve the track irregularity detection accuracy.

2. The Principle of Inertial Reference Method Detection

Inertial reference method [9] [10] measuring system is in the moving car, speed meter and gyroscope is used to establish an inertial reference benchmark, through the measurements of these two kinds of inertial components analytical method to get a benchmark, and reuse displacement sensor or image sensor measurement orbit relative position relative to the benchmark, and get the relative position at the top of the rail in the inertial coordinate system.

As shown in **Figure 1**, under the same datum point, according to the basic principle of strap down inertial navigation system [11] [12], using the angular velocity signal output by gyroscope, real-time updating the attitude matrix of the carrier, through the attitude matrix we can transform the acceleration signal output from accelerometer into the geographical coordinate system, and can get the trajectory curve of three axis x, y, z in geographic coordinate system after two integral operation for acceleration signal. The curve of x, y, z respectively represents projection parameters of rail lines in the vertical plane and horizontal plane and vertical plane, further combined with results of the cross section measurement system, ultimately get all the irregularity parameters we need [13] [14]. Through comparing the different results to acquire the deviation, the deformation can be calculated quantitatively, so that the workers can repair the serious abrasion timely. Moreover, during the actual measurement, what's mainly concerned is the rail deformation of vertical and level plane, meaning the irregularity value of height and direction.

3. Empirical Mode Decomposition Algorithm

The basic method of empirical mode decomposition: Through continuous screening, the complex signal is decomposed into several intrinsic mode functions IMF component which are arranged from high to low frequency and the residual term, as shown in Equation (1), the concrete process can be referred to [15].

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r_n(t) \tag{1}$$

r_n is residue component, representing average trend of the signal. And each IMF component $IMF_1(t)$, $IMF_2(t)\cdots, IMF_n(t)$ respectively contains different frequency signal components from high to low.

After decomposition, each intrinsic mode function (IMF) must be met two conditions following: 1) Throughout the time sequence, the number of passing zero is equal to the number of the pole or at best, a difference; 2) At any point, the mean value composed of local maximum value upper envelope and lower local minima envelope must be zero.

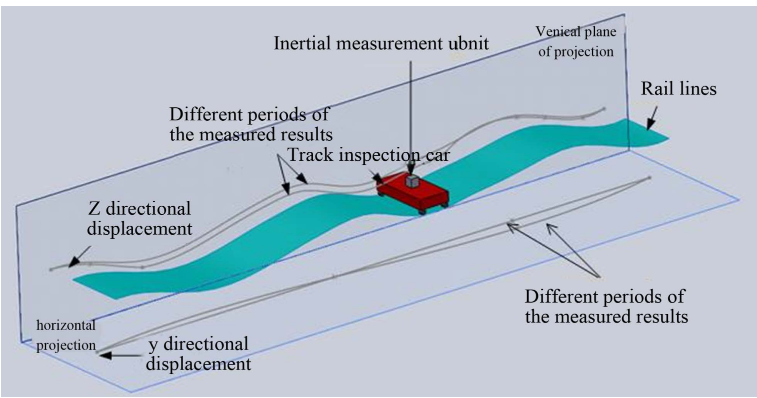


Figure 1. The image of motion trajectory.

After EMD decomposition we can get finite IMF: Among them, the big order corresponding to the low frequency component signals, is generally thought that little impact noise in the low frequency components; Small order corresponds to the high frequency component signal, often assume that contains a sharp part of the signal and noise [16] [17]. The main idea of using EMD method to deal with the noise is that main energy of most polluted signals is concentrated in low frequency band, the farther the high frequencies, it contains the less energy, so we can reconstruct signal partly by using several IMF in low frequency, namely:

$$\tilde{x}(t) = \sum_{i=K+1}^{N} IMF_i(t) \tag{2}$$

4. An EMD De-Noising Method Based on the Statistical Characteristic

4.1. Random Noise Power Statistical Properties

For the length of N discrete signal $x(n)$, the power calculation formula is:

$$P_x = \frac{1}{N}\sum_{i=1}^{N} x^2(n_i) \tag{3}$$

If keep the amplitude of original signal $x(n)$ each element constant, to disrupt its location in order to get $x'(n)$, $x(n)$ and $x'(n)$ can be determined power equal, namely, $P_x = P_{x'}$, the signal power stays the same after a random sequence.

The following research is the changing rule of the noise power through random noise $n(t)$ after the "random sort-accumulative-average". Stochastic scheduling random noise $n(t)$ which sampling points is 2048 , totally 25 times repeated, after the i time random sort we can get the new noise $n_i(t)$, superimpose $n_i(t)$ and the noise $n_i(t)$ which is get from random sequence of i-1 before, can obtain a new noise component:

$$n_i' = \frac{n(t) + \sum_{j=i}^{i} n_j(t)}{i+1} \tag{4}$$

Computing the power of $n_i'(t)$ by Equation (3), then we can get a power—sort frequency curve, as shown in Figure 2. In Figure 2, the power $P_{n'}$ gradually reduced with the increase of number of sorting number i after the "random sort-accumulation-average"; when sorting number i increased to a certain degree, the attenuation speed of power $P_{n'}$ became slow; when i tend to be infinite, $P_{n'}$ will be close to zero.

Inspired by the above experiments, we let the ***imf***$_1$, ***imf***$_2$, ***imf***$_3$ component which is obtained after the EMD decomposition of the random noise $n(t)$ "random sort-accumulative-average" and compute power, the power-sort frequency curve respectively as shown in Figures 3(a)-(c).

Experimental results show that the first IMF component of random noise after EMD decomposition remains the approximate random features, for the first IMF component namely the ***imf***$_1$, in accordance with the "random sort-average accumulative" the new noise power decreases with the increase of number of random sequence.

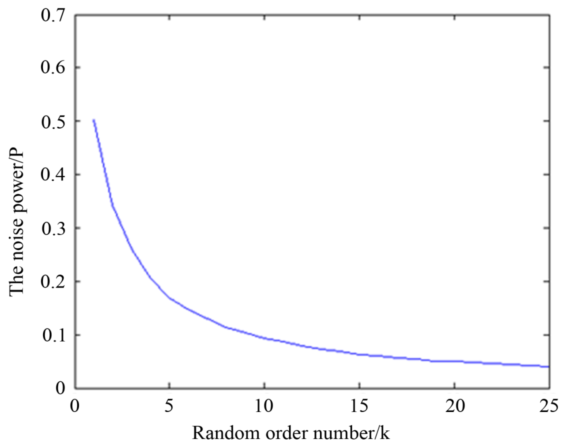


Figure 2. Noise power-sort frequency curve.

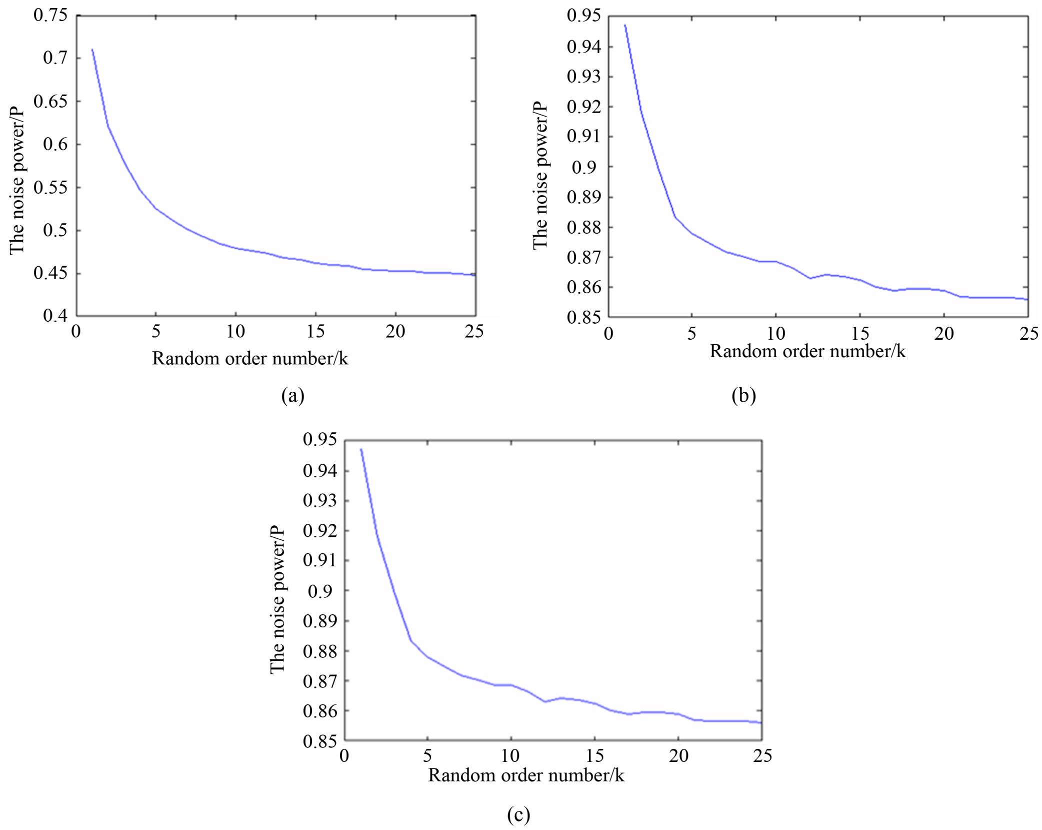


Figure 3. Noise IMF component power-sort frequency curve.

4.2. The Statistical Feature of Random Noise Autocorrelation Function

The autocorrelation function of random signal is an average measure of the signal time domain features, reflecting the signal related degree at two different times t_1, t_2. Random signal $x(t)$ autocorrelation function is defined as:

$$R_x(t_1, t_2) = E\left[x_1(t)x_2(t)\right] \tag{5}$$

The autocorrelation function of random noise $n(t)$ and general signal $x(t)$ can be calculated respectively according to the Equation (5), function curve as shown in Figure 4 and Figure 5, respectively.

$$\rho_\tau = \frac{R_x(\tau)}{R_x(0)} \tag{6}$$

where $\tau = t_1 - t_2$, represent time difference.

The Figure 4 and Figure 5 show that although the normalized autocorrelation function of random noise $n(t)$ and $x(t)$ can get maximum value in zero, but outside the zero point is different; For random noise $n(t)$, because of its weak correlation and randomness in every moment, so its maximum of autocorrelation function can get at zero, autocorrelation function at other points attenuation quickly to small features; For the general signal $x(t)$, its autocorrelation function does not have such features. Using this feature can determine the cut-off point in the signal-to-noise ratio (SNR) dominant mode.

4.3. The EMD De-Noising Algorithm Based on Noise Statistical Properties

According to the statistical characteristics analysis of random noise power, autocorrelation function [18], put forward "the EMD de-noising algorithm based on noise statistical characteristics" and use "sort-accumulation-average-refactoring" order to suppress the noise. Specific steps are as follows:

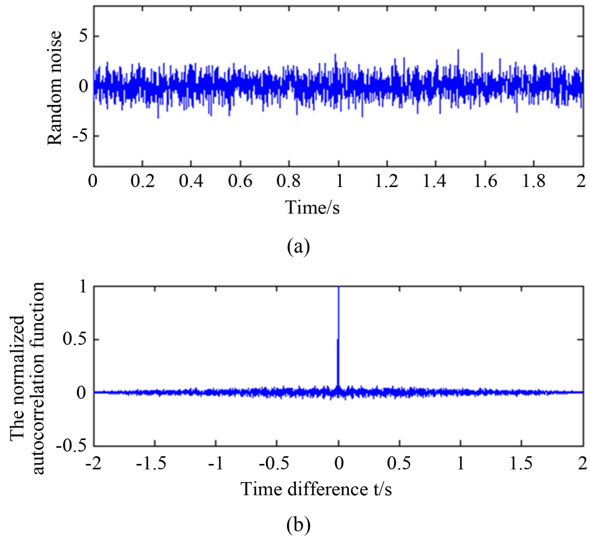


Figure 4. Noise and normalized autocorrelation function.

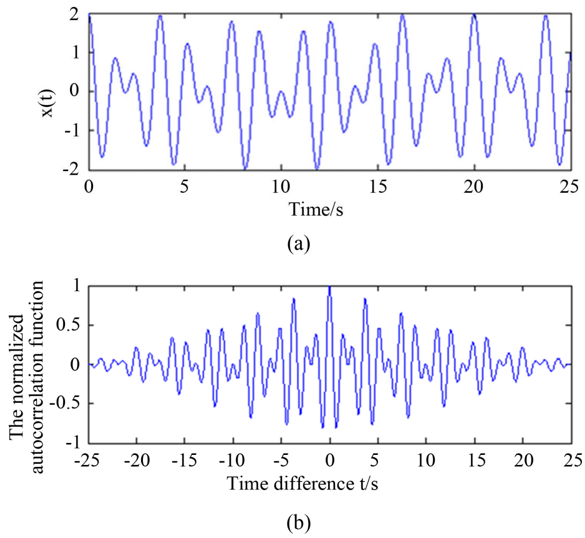


Figure 5. Signal *x* (*t*) and normalized autocorrelation function.

Step 1: the EMD decomposition on noise signal $y(t)$, get N intrinsic mode components IMF, and let the last trend item quantity decomposed for the first N IMF;

Step 2: remember $n(t)=imf_1(t)$, $x(t)=\sum_{i=2}^{N} imf_i(t)$, $n_{\text{cumulate}}(t)=n(t)$;

Step 3: stochastic scheduling $n(t)$ and get a new component $n_1(t)$, namely $n_{\text{cumulate}}(t)=n_{\text{cumulate}}(t)+n_1(t)$;

Step 4: repeat Step 3 R times, calculate the average of accumulation to get a new noise dominant mode $n_R(t)=\dfrac{n_{\text{cumulate}}(t)}{R+1}$ which power is weaken;

Step 5: get a new noise signal $y_1'(t)=n_R(t)+x(t)$ which signal-to-noise ratio is improved after the refactoring of $n_R(t)$ and $x(t)$;

Step 6: $y_1'(t)$ should be considered the original pollution signal repeat Steps 1 - 5 S times, get further suppressive noise signal $y_2'(t)$;

Step 7: EMD decomposition on $y_2'(t)$ first, then calculate the autocorrelation function of the N IMF component, based on the characteristics of the autocorrelation function graphic judge the cutoff point K of noise dominant mode and the signal dominated mode;

Step 8: global threshold selection method on the noise dominant mode component $imf_1(t) \sim imf_K(t)$ to deal with the noise, namely:

$$imf_i' = \begin{cases} \operatorname{sgn}\left(imf_i(j)\left(\left|imf_i(j)\right|\right) - T_i\right), \left|imf_i(j)\right| > T_i \\ 0 \qquad\qquad\qquad\qquad\qquad , \left|imf_i(j)\right| \le T_i \end{cases}$$

where $T_i = \sigma_i \sqrt{2 \ln L}$ is the threshold value of the *i*th component $imf_i(t)$, L is the length of signal, σ_i is the standard deviation of $imf_i(t)$, namely $\sigma_i = \frac{1}{L}\sum_{j=1}^{L}\left(imf_i(j) - \overline{imf_i(t)}\right)^2$;

Step 9: refactoring on $imf_1'(t) \sim imf_K'(t)$ and $imf_{K+1}(t) \sim imf_N(t)$, then we can get de-nosing signal $y'(t)$.

5. Experimental Verification

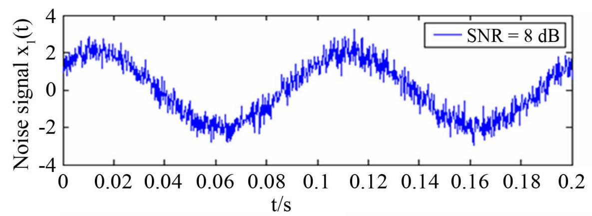
5.1. Analog Signal

Using the method to deal with the noise of $x_1(t)$ and $x_2(t)$ which contains Gaussian white noise in different SNR, among them, $x_1(t)$, $x_2(t)$ results from the superposition of gauss white noise of signal

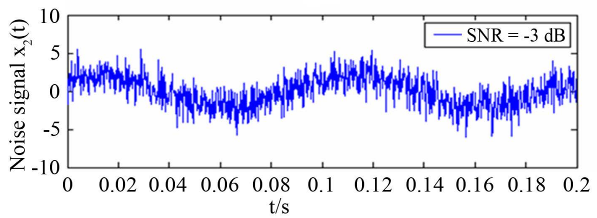
$$f(t) = 2\sin\left(20\pi t + \frac{\pi}{4}\right),$$

SNR of $x_1(t)$ is 8 dB, SNR of $x_2(t)$ is −3dB, as shown in **Figure 6(a)** and **Figure 6(b)**. To the EMD decomposition of $x_1(t)$ and $x_2(t)$, "random sort-accumulation-average" on the first *imf* component for R times, with the rest of the *imf* component refactoring again, continue to repeat S times ($x_1(t): R = 45, S = 3$; $x_2(t): R = 45, S = 3$), then can get signal $x_1'(t)$, $x_2'(t)$ which SNR is improved, as shown in **Figure 7(a)** and **Figure 7(b)**.

Continue to the EMD decomposition on $x_1'(t)$, $x_2'(t)$, and calculate the autocorrelation function of each *imf* component, as shown in **Figure 8(a)** and **Figure 8(b)**. The random noise autocorrelation function statistical properties is used to select the SNR cut-off point $K_1 = 5$, global threshold selection method on $imf_1(t) \sim imf_5(t)$ to deal with the noise and get $imf_1'(t) \sim imf_5'(t)$, refactoring on $imf_1'(t) \sim imf_5'(t)$ and $imf_6(t)$ to get signal $X_1'(t)$, as shown in **Figure 9(a)**; In the same way, select SNR cut-off point $K_2 = 5$, refactoring and get signal $X_2'(t)$, as shown in **Figure 9(b)**. The difference between $X_2'(t)$ at both ends in **Figure 9(b)** and the original signal $X_2(t)$ is caused by the inherent defects—endpoint effect of the EMD decomposition algorithm.



(a)



(b)

Figure 6. Noisy signals.

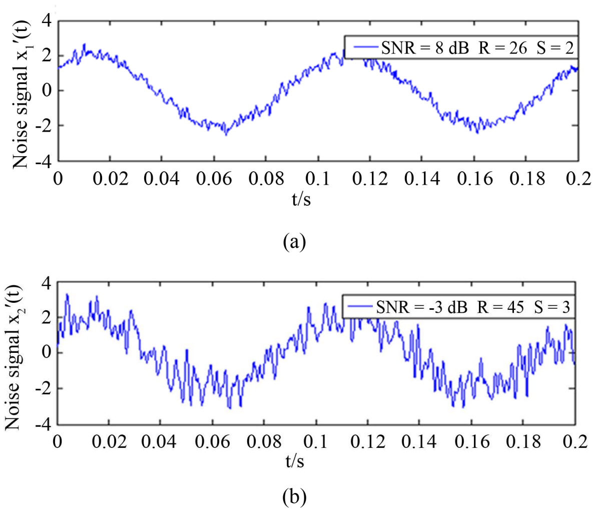


Figure 7. De-nosing results of test signals.

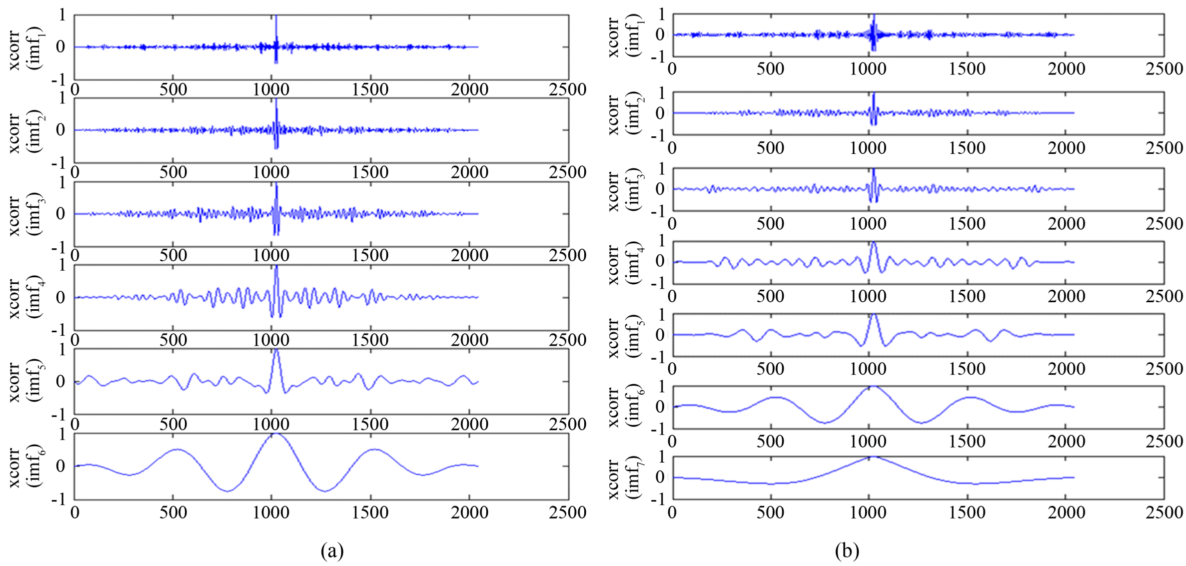


Figure 8. Each *imf* component of normalized autocorrelation function of $x_1'(t)$ and $x_2'(t)$.

Through the simulation experiments analysis: under the condition of low signal noise ratio (SNR), the EMD de-noising algorithm based on random noise statistical characteristics still can obtain good de-noising effect.

5.2. The Experiment Results Analysis

Experiment system uses XW-IMU5250 tiny mechanical inertial device of Beijing StarNeto Technology Development Co., Ltd. In the experiments for loading of the inertial measurement unit testing the car through an analog line segments, and then collect the inertial measurement unit acceleration along *x*, *y*, *z* axis among the car movement. First of all, using the average filtering method to eliminate the acceleration signal contained in the direct current; this method is applied to the actual inertial unit signal noise processing then. The waveform and spectrum diagram of de-noising before and after as shown in **Figures 10-12**.

Integral operation on *x*, *y*, *z* axis acceleration signal after de-noising, and through the attitude matrix transforms the movement information of vehicle coordinates to geographic coordinates, and get the car's trajectory, the experimental results and the actual test vehicle by rail sections as shown in **Figure 13**, error range within ±0.5 mm.

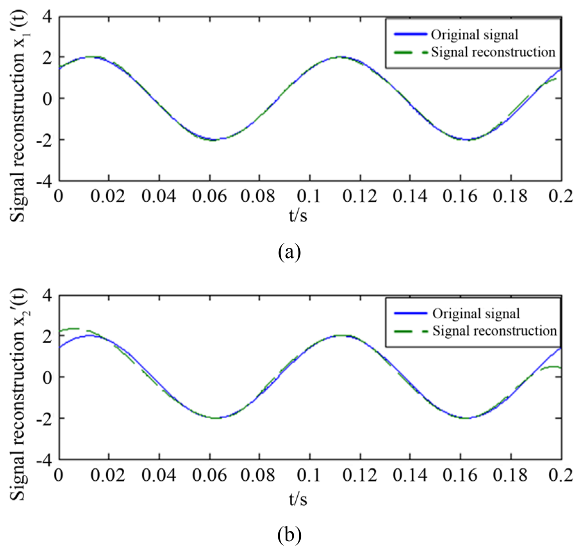


Figure 9. De-nosing result of the proposed method.

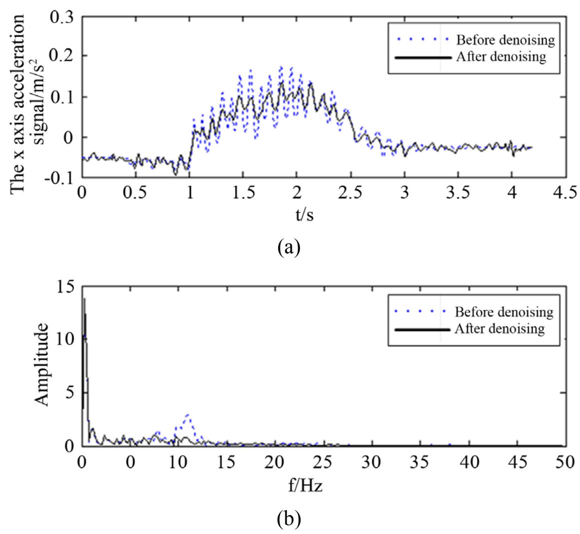


Figure 10. The waveform and spectrum diagram of de-noising before and after of *x* axis acceleration signal.

6. Conclusion

In this paper, by using the random noise power, autocorrelation function statistical characteristics, a kind of suitable for low SNR signal de-noising method is put forward. The method can get the first component of the IMF after EMD decomposition on noise signal, in accordance with the "random sort-accumulation-average-reconstruction" order. We can get a reconstruction signal whose noise power is significantly weaken and signal power constant firstly, and then do EMD decomposition again for the reconstructed signal, and determine the cut-off point of signal-to-noise dominant mode by using signal autocorrelation function characteristics, realize the final de-noising signal reconstruction. Test results show that in low signal noise ratio (SNR) the method for de-noising effect is obvious. At the same time, good performance of inertial measurement unit in the treatment of orbital state detection signal provides a new thought for the future of inertial measurement unit signal processing.

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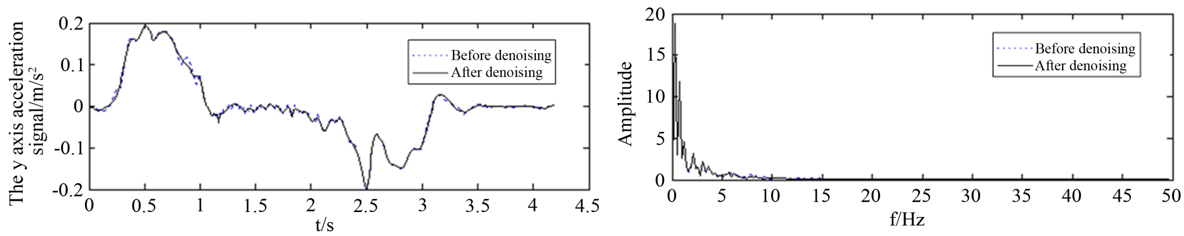
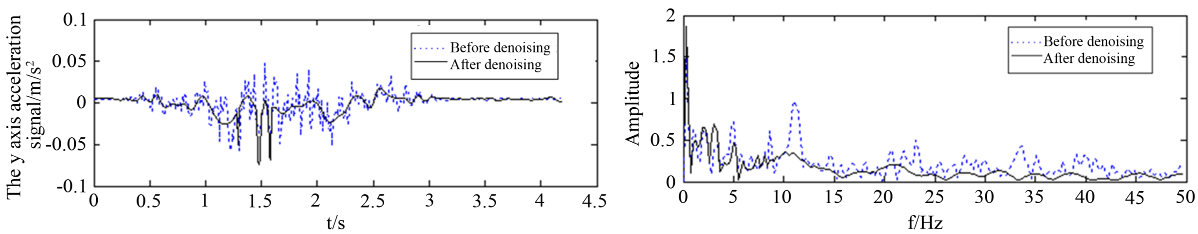


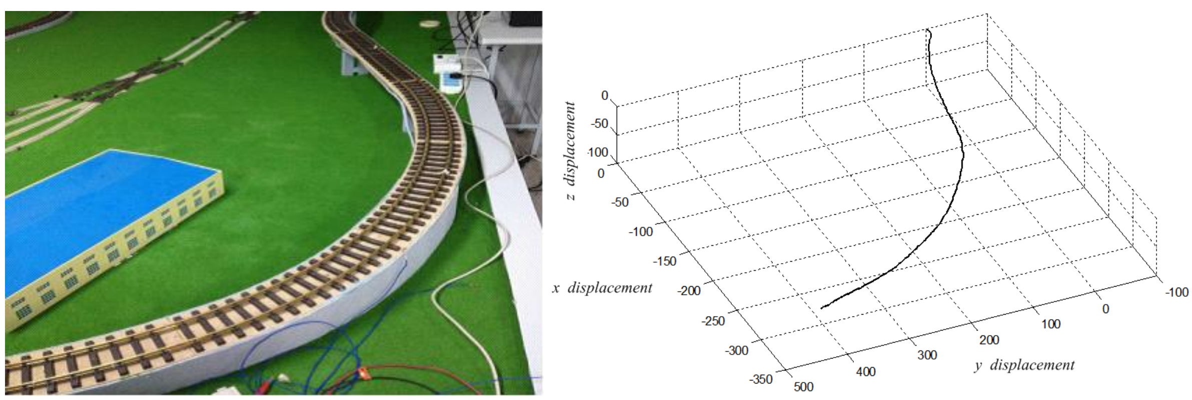
(a) (b)

Figure 11. The waveform and spectrum diagram of de-noising before and after of *y* axis acceleration signal.



(a) (b)

Figure 12. The waveform and spectrum diagram of de-noising before and after of *z* axis acceleration signal.



(a) (b)

Figure 13. Experimental platform orbit and space displacement curve after two integrals.

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