Non-stationary vibration road spectrum reconstruction of wheeled vehicles based on FCM clustering wavelet packet coefficient matrix

Zongkai Liu¹, Xiaoqiang Yang¹*, Jinxing Shen¹
¹Field Engineering College of Army Engineering University, Nanjin 210007, China
*Corresponding Author’s e-mail: yangxqlab@163.com

Abstract: In this paper, a frequency domain non-stationary vibration spectrum simulation reconstruction method is proposed, which based on Fuzzy C-Means (FCM) clustering wavelet packet coefficient matrix reconstruction. The factors such as the non-stationarity of the road surface excitation and vibration response of the vehicle due to the time variation of the vehicle speed and the nonlinearity of the coupled vibration of the vehicle body during the running of the wheeled vehicle are considered. In this method, the one-dimensional measured vibration spectrum reconstruction problem is turned into the two-dimensional wavelet packet coefficient matrix (image) reconstruction problem by wavelet packet transform. Furthermore, based on the FCM clustering principle of wavelet packet coefficient normalized column vector, some non-stationary features in the frequency domain was extracted to realize the frequency domain non-stationary reconstruction of the measured road spectrum, including the important vibration types contained in the measured vibration spectrum and the total probability of occurrence and the adjacent conditional probability, and the dispersion around the cluster center in each type. Through the comparison with the measured road spectrum, the method was verified that it can accurately simulate the actual road driving conditions of the wheeled vehicle. The reconstructed road spectrum this method provided is consistent with the actual working conditions for road simulation experiments.

1. Introduction
Compared with the actual road test, the laboratory road simulation test can reproduce the road excitation accurately and continue uninterruptedly. It not only has the advantages of saving time and economic cost, but also has good controllability, strong repeatability and high precision standard, which is an ideal experimental method [1]. It is worth mentioning that due to the limitations of the collection of test sites and equipment, the real vehicle response spectrum collected within a limited mileage often cannot meet the hundreds or even hundreds of thousands of kilometers of travel on the road simulation test bench or virtual simulation environment. Therefore, when performing road simulation tests, the actual input test bench as an excitation is often a reconstructed spectrum reconstructed from certain features of the acquired spectrum. Only by constructing accurate road spectrum data close to the actual road conditions can the real effect of the simulation experiment be achieved. The road excitation originates from the road roughness. According to the mathematical definition, the road roughness is a typical random function, and it is a random process with time as a parameter with respect to a constant vehicle speed [2]. The stochastic process can divided into a stationary process and a non-stationary process according to the characteristics.
Based on the assumption of stationary random Gaussian process, researchers have done a lot of research on road spectrum reconstruction, and proposed a variety of road spectrum reconstruction methods, such as the harmonic superposition method [3], the filtering white noise method [4], the inverse Fourier transform method [5] and the time series model method [6], etc. Firstly, Harmonic superposition method is a commonly used reconstruction method which uses the discrete Fourier transform to decompose the road spectrum of a given power spectral density into a series of sine waves with different frequencies and amplitudes. And it is especially suitable for generating standard roads. Secondly, the filter white noise method converts white noise that satisfies a specified spectral feature into a random white noise random road sequence by an integrator or a shaping filter, that is, obtains a time domain road roughness sequence. Besides, the inverse Fourier transform method is to transform the road spectrum of a given power spectral density into a time domain road roughness sequence by using the inverse Fourier transform. Moreover, the time series model method is based on the measured road roughness data to establish a time series model (AR or ARMA model), and predict the road roughness sequence [7].

However, in actual driving conditions, wheeled vehicles are more extreme off-road roads with frequent high amplitude impacts and significant non-Gaussian characteristics [8]. In addition, during the driving process, the non-stationary random excitation caused by the change of the vehicle speed and the nonlinearity of the vehicle body coupling is mainly manifested by the non-stationary vibration response of the wheeled equipment. (In a broad sense, the road spectrum not only refers to the power spectral density of road roughness, but also the vibration response of wheel equipment under road excitation can also be called “generalized road spectrum”, both of which can be used as input for road simulation experiments). For the research of the non-stationary non-Gaussian random signals, Rouillard et. al proposed a method of combining Gaussian stochastic processes with different root mean squares and time lengths, which could simulate the generation of the non-stationary non-Gaussian signals obeying the specified power spectral density and root mean square distribution function[9-11].Wen et.al proposed a simulation method based on the Hilbert-Huang transform to propagate ground vibrations, which can generate the signals with time-varying characteristics of frequency and amplitude[12].

Based on the analysis of the non-stationary random road and wheeled equipment response, this paper proposed a method based on FCM clustering wavelet packet transform to reconstruct non-stationary random road spectrum.

2. Road spectrum acquisition experiment

2.1 Road spectrum data collection

This paper selects a wheeled vehicle with active suspension as the test collection object. A road spectrum measurement system was designed to measure the road condition of the wheeled vehicle and the excitation response of the road to the wheeled vehicle [13-14]. As is shown in Figure 1, it is the structural schematic diagram. According to the Nyquist sampling theorem, the sampling frequencies of acceleration and road profile data were set to 1kHz, while the sampling frequency of gyro attitudes was set to 200Hz. The designed road spectrum measurement system includes multi-channel signals, such as four-channel vibration acceleration signals, four-channel displacement signals, three-channel attitude angle signals, four-way GPS trajectory signals and so on. The vibration acceleration signals of the axle head are the main data for testing and analyzing in this paper.
Considering that the actual driving environment of wheeled vehicles is more complicated and diverse, the road spectrum collection test should also be tested and analyzed for different roads, including high-speed loop roads and cement roads with good road conditions, and enhanced roads with poor road conditions, and so on. This paper has selected a number of test sites for testing. The main road types collected include asphalt road, cement road, block stone road (Belgian road), gravel road, and pothole road. Figure 2 is a partial acceleration original signal curve corresponding to the block stone path and Figure 3 shows the block road pavement.

2.2 Data preprocessing
The collected data contains many accidental error factors which are not conducive to analysis, such as sensor error, uneven road conditions, unstable operation and environmental noise interference. Therefore, in this paper, after the load spectrum measurement, the improved Leinda criterion was used to eliminate the outliers, and the EMD empirical mode decomposition method was used to eliminate the trend term and the DC component [15-17]. Finally, the data is resampled by low pass filtering.

Taking the axle acceleration collected from the wheeled vehicle through the stone path of a test field as an example. Figure 4(a) shows the overall comparison chart (In the above is the measured curve, and below is the pre-processed curve), Figure 4(b) is the local comparison chart, it can be clearly seen that the singular points and trend terms have been eliminated on the pre-processed curve and can speed up subsequent analysis.
3. Wavelet packet transform and FCM clustering

3.1 Wavelet packet transform

Wavelet packet transform is developed on the basis of wavelet transform, and the high-frequency part without multi-resolution analysis is also processed [18]. Therefore, compared with the wavelet transform, the wavelet packet transform is more suitable for decomposing and synthesizing the vibration spectrum of the wheeled vehicle that must be accurately analyzed in the whole frequency band after preprocessing such as low-pass filtering.

The wavelet packet can be described by a three-layer decomposition. The wavelet packet decomposition tree is shown in Figure 6 where L represents a low frequency, H represents a high frequency, and the number is expressed as the number of layers in which the wavelet packet is decomposed. Then the decomposition relationship is expressed as \( S = L_3^1 + H_3^1 + L_3^2 + H_3^2 + L_3^3 + H_3^3 + L_3^4 + H_3^4 \).

![Wavelet packet decomposition tree](image)

Figure 5. Wavelet packet decomposition tree

Actually, wavelet packet decomposition of discrete signals is usually performed using the Mallat fast algorithm [19]:

\[
\begin{align*}
  d_0^j[l] &= \sum_{k \in \mathbb{Z}} h_0[l - 2k]d_0^j[l] \\
  d_1^j[l] &= \sum_{k \in \mathbb{Z}} h_1[l - 2k]d_1^j[l]
\end{align*}
\]

(1)

And the recursive algorithm for wavelet packet reconstruction is:

\[
d_j[l] = \sum_k \{H_0[l - 2k]d_{j+1}^0[k] + H_1[l - 2k]d_{j+1}^1[k]\}
\]

(2)

where \( h_0, h_1, H_0 \) and \( H_1 \) are the low-pass and high-pass filter coefficients for wavelet packet decomposition and reconstruction (depending on the type of wavelet packet base selected). Assuming \( N \) can be divisible by \( 2^j \) and the quotient is \( n \), then \( d_j^1[k] \mid_{k=1,2,\ldots,n} \) is the i-th wavelet packet coefficient on the j-th layer, and \( d_0^0[k] = f[k] \). It should be noted that the above arrangement order \( i.j \) is a natural
order. For ease of analysis, the wavelet packet number $i$ is arranged in order of frequency. When considering only the wavelet packet coefficients on the $j$-th layer, $d_j[k]$ can be abbreviated as a two-dimensional matrix $D_j$ of size $2^j \times n$. That two-dimensional wavelet coefficient matrix is:

$$D_j = \begin{bmatrix}
    d[1,1] & d[1,2] & \cdots & \cdots & d[1,n] \\
    d[2,1] & d[2,2] & \cdots & \cdots & d[2,n] \\
    \vdots & \vdots & \ddots & \cdots & \vdots \\
    \vdots & \vdots & \cdots & d[i,k] & \vdots \\
    \vdots & \vdots & \cdots & \cdots & d[2^j,1] & d[2^j,2] & \cdots & \cdots & d[2^j,n] \\
\end{bmatrix}$$  \hspace{1cm} (3)

In order to display the time-frequency characteristics of the signal more clearly, the above-mentioned wavelet coefficient matrix (also called time-frequency image) is usually drawn in an image form according to its value. At this time, according to the wavelet packet transform property, the $j$-th layer wavelet packet decomposition is performed on the signal of the sampling frequency $F_s$ and the time-frequency resolutions are respectively:

$$\begin{align*}
    \Delta t &= 2^j/F_s \\
    \Delta f &= F_s/2^{j+1}
\end{align*}$$  \hspace{1cm} (4)

It can be seen that as the number of layers $j$ increases, the wavelet packet decomposition time resolution $\Delta t$ decreases and the frequency resolution $\Delta f$ increases together.

The above load spectrum is selected as an example for analysis, as shown in Figure 6 (a), and the frequency after resampling is 128 Hz. Selecting the db6 wavelet packet to perform 6-level decomposition to obtain the wavelet packet coefficient image is shown in Figure 6(b). From equation (4), we can know the time/frequency resolution of the image is 0.5s/1Hz.

![Figures 6. Vibration spectrum of block stone road wheel vehicle and its wavelet packet coefficient image](image)

It can be known from equation (3) that the row vector composed of the coefficients of the $i$-th row is

$$r_i = \{d[i,1], d[i,2], \cdots, d[i,n]\}$$  \hspace{1cm} (5)

which represents the change in signal energy over time in the band $[(i-1)\Delta f, i\Delta f]$, and the sum of the squares of the coefficients above it is:

$$E_r[i] = r_i \cdot r_i^T = \sum_{k=1}^{n} d^2[i,k]$$  \hspace{1cm} (6)

where $E_r[i]$ represents the generalized energy of the signal in this band. According to the Parseval’s theorem, it has the following correspondence with the power spectral density (PSD) function $P(f)$ of the signal:

$$E_r[i] = C_\phi \int_{(i-1)\Delta f}^{i\Delta f} P(f) \, df$$  \hspace{1cm} (7)
where $C_\phi$ is a constant related to the type of wavelet packet base.

So, in the all frequency bands there is:

$$
\sum_i E_r[i] = C_\phi \int_0^{R_e^2} P(f) \, df \tag{8}
$$

Equations (7) and (8) illustrate that the sum of the squares of the wavelet packet coefficients directly reflects the strength of the signal energy in the band. Similarly, for the $k$-th column coefficient vector in the coefficient matrix and its sum of squares are:

$$
c_k = [d[1, k], d[2, k], \ldots, d[2^j, k]]^T \tag{9}
$$

$$
E_c[k] = c_k^T \cdot c_k = \sum_{i=1}^{2^j} d^2[i, k] \tag{10}
$$

where $c_k$ and $E_c[k]$ represent the generalized instantaneous power spectrum and the generalized instantaneous energy of the signal during the period $[(k - 1)\Delta t, k\Delta t]$ respectively.

For the convenience of analysis, the wavelet packet coefficient row/column coefficient vectors shown in equations (5) and (9) are also respectively normalized:

$$
\begin{bmatrix}
\tilde{r}_l = r_l / \max(r_l) \\
\tilde{c}_k = c_k / \max(c_k)
\end{bmatrix} \tag{11}
$$

Figures 7 shows the row vector and column vector images normalized by the wavelet packet coefficients as shown in Figure 6.

Figures 7. Wavelet packet normalization coefficient vector image

It can be seen from the normalized line vector image in Figure 8(a) that the intensity of the wheeled vehicle vibration response in all frequency bands can be considered to be stable when the road surface conditions are single. On the other hand, the normalized column vector image shown in Figure 8(b) shows obvious non-stationary characteristics, indicating that the instantaneous power spectrum of the vibration spectrum has obvious time-varying characteristics.

3.2 Reconstruction of wavelet packet coefficient matrix based on FCM clustering

At present, the intensity stability of the vibration response of a wheeled vehicle while traveling on a road can be quantitatively checked by various methods. However, the stability of the power spectrum can only be qualitatively analyzed by time-frequency analysis methods (such as wavelet packet transform, short-time Fourier transform, etc.). Since the factors affecting the non-stationary nature of the vibration spectrum of the wheeled vehicle (including accidental excitation sources, vibration transmission paths, etc.) are limited, the normalized column vector $\tilde{c}_k$ can be regarded as a “curve”, thus the FCM clustering method is used to cluster the set of all normalized column vectors. When the number of clusters is $n$, the instantaneous power spectrum of the original signal can be divided into $n$ different "types", which serves as the preliminary basis for determining the non-stationarity.
3.2.1 FCM clustering of normalized column vectors

FCM clustering is a clustering algorithm that determines the degree of a cluster to which a sample belongs based on membership degree [20]. For the total of \( n \) normalized column vector sets \( \{\tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_n\} \), suppose it can be divided into \( M \) \((1 \leq M \leq n)\) classes and correspondingly there are \( M \) cluster centers (vectors). The membership degree of any normalized column vector \( \tilde{c}_{i} \) for the \( i \)-th cluster center is defined as \( u_{ik} \) and \( \sum_{i=1}^{M} u_{ik} = 1 \). Then define the objective function of FCM as:

\[
J = \sum_{i=1}^{M} \sum_{k=1}^{n} u_{ik}^m \left\| \tilde{c}_k - c_{center}\right\|^2 (12)
\]

The objective function indicates the weighted distance of each sample from the center of the fuzzy cluster. Where \( m_f \) is a weighted index that affects the degree of fuzzification of the membership degree matrix, usually taking \( m_f = 2 \). The goal of FCM is to select the appropriate cluster center \( \tilde{c}_k \) and membership degree \( u_{ik} \) by iteration, so that the distance weighted sum of the cluster center is the smallest. The specific process is shown in Figure 8:

![Figure 8. FCM cluster center selection](image)

(1) Randomly generate \( M \) initial cluster centers, \( \{c_{center}^0, c_{center}^1, \ldots, c_{center}^M\} \);  
(2) Calculate membership degrees:

\[
u_{ik} = \frac{1}{\sum_{i=1}^{M} \left( \frac{\left\| \tilde{c}_k - c_{center}^{i}\right\|^2}{\left\| \tilde{c}_k - c_{center}^{i}\right\|^2} \right)^{\frac{1}{m_f-1}}} (13)
\]

(3) Modify the cluster centers:

\[
center^1 = \frac{\sum_{k=1}^{n} (u_{ik})^m \tilde{c}_k}{\sum_{k=1}^{n} (u_{ik})^m} (14)
\]

(4) Judge whether the cluster center converges: for a specified small enough value \( \xi \), if \( \sum_{i=1}^{M} \left\| c_{center}^1 - c_{center}^0 \right\|^2 \leq \xi \), the algorithm ends; otherwise, make \( c_{center}^0 \leftarrow c_{center}^1 \) and repeat steps (2) and (3).

3.2.2 FCM clustering of normalized column vectors

After FCM clustering calculation, the \( n \) sets of column vectors will be classified into \( m \) \((m \leq M)\) categories, sorted according to the number of column vectors included in the category. The number of column vectors included in each category is \( n_c^i | i = 1, 2, \ldots, m \), and its corresponding cluster center (curve) is \( c_{center}^i | i = 1, 2, \ldots, m \). In order to perform normalized column vector reconstruction, further statistics should be made on the clustering results:
(1) Define a square matrix of \( m \times m \) dimensions, where each element \( p_{ij} \) represents the first-order adjacent conditional probability of the \( j \)-th column vector appearing after the \( i \)-th column vector, and defines its cumulative probability \( p_{cum-ij} = \sum_{j \leq j} p_{ij} \).

(2) Calculate the degree of diffusion of each normalized column vector belonging to each category relative to the cluster center. In the absence of assumptions about the distribution characteristics of the diffusion, this paper uses the percentile to make separate statistics for each point on the curve: For the \( k \)-th value on all normalized column vectors on the \( i \)-th classification (corresponding to the corresponding column normalized wavelet packet coefficients), counts several percentile points: \( \{Q_{ik-q_1}, Q_{ik-q_2}, \ldots, Q_{ik-q_n}\} \) \( (0 < q_1 < q_2 < \ldots < q_n \leq 100) \), as the basis for subsequent segmentation random reconstruction.

After the above statistics and analysis of the clustering results are completed, the normalized column vector can be reconstructed:

1. Specify the class sequence of each reconstructed normalized column vector and make the adjacent probability \( p_{ij} \).
2. Generate a reconstructed normalized column vector curve according to the predetermined classification sequence, and each reconstruction curve satisfies the distribution pattern of the column vector in each category in the original clustering result around its cluster center.

### 3.3 Wavelet Packet Coefficient Matrix Reconstruction

For the reconstructed normalized column vector matrix that has been generated, it only needs to supplement its intensity information to restore it to the reconstructed wavelet packet coefficient matrix. Since the generalized instantaneous energy shown in equation (10) is considered to be stationary, the work of reconstructing the wavelet packet coefficient matrix can be completed by using the generalized energy information of the original wavelet packet coefficient matrix. The specific steps are as follows:

1. Calculating the original wavelet packet coefficient matrix generalized instantaneous energy sequence \( E_c[k] \) \( (k = 1, 2, \ldots, n) \) from equation (10) and calculate the distribution characteristics and generate reconstructed generalized instantaneous energy sequences \( E_c^*[l] \) \( (k = 1, 2, \ldots, n) \) according to the distribution features. Experience has shown that the generalized instantaneous energy of most measured road spectrums can generally be described by stochastic distributions such as lognormal distribution, gamma distribution, and Weibull distribution, etc.
2. Assign the reconstructed generalized instantaneous energy to each reconstructed normalized column vector:

\[
E^*[l] = \frac{\tilde{E}_c^*[l]}{\tilde{E}_c[l]} \cdot \tilde{c}_i^* \tag{15}
\]

where \( \tilde{E}_c^*[l] \) is the generalized instantaneous energy of each reconstructed normalized vector: \( \tilde{E}_c^*[l] = \tilde{c}_i^T \cdot \tilde{c}_i^* \).

The reconstructed wavelet packet coefficient matrix is composed of a reconstructed column vector sequence \( [\tilde{c}_1^*, \tilde{c}_2^*, \ldots, \tilde{c}_n^*] \), and the reconstructed vibration spectrum can be obtained by using the matrix to reconstruct the wavelet packet represented by the equation (2). Finally, according to the nature of wavelet packet transform, by optimizing the different wavelet packet types and decomposition layers, the reconstructed vibration spectrum will have ideal time-frequency characteristics similar to the original acquisition spectrum.

### 4. Non-stationary vibration spectrum reconstruction

In order to verify the feasibility of the proposed reconstruction algorithm, the vibration response spectrum (as shown in Figure 5(a)) collected on the block stone road was taken as an example. According to the method in the previous section, the normalized column vector image shown in Figure 7(b) is represented by a curve set form (Figure 9). The figure shows a set of normalized instantaneous
power spectral lines with a time/frequency resolution of the original vibration response signal of 0.5 s/1 Hz.

Figure 9. Normalized wavelet packet coefficient vector (Partial)

Then, the normalized column vector curve was clustered by the FCM clustering algorithm to form nine effective classifications. Based on the peak frequency of the cluster center, the range of peak frequency variation, and the strength of the medium and high frequency components, the nine effective classifications can be further divided into four categories, as shown in Figures 10.

(a) Class I (2nd, 3rd effective classification) (b) Class II (4th, 6th effective classification)

(c) Class III (1st, 7th effective classification) (d) Class IV (effective classifications 5, 8, 9)

Figures 10. Cluster center

As can be seen from the Figure 10, the Class I center curve has sharp peaks, which represents the ideal wheel equipment vibration response where the influence of various external nonlinear factors is small and the wheeled equipment runs smoothly. Besides, the slight change of the peak frequency of the center curve indicates that the structural dynamics parameters of the wheeled vehicles vibration system have slight nonlinear changes. Secondly, the Class II center curve has one strong peak and one weak peak, which represents a relatively strong influence of the vibration of the collection by an external (the opposite side of the wheel) excitation. Thirdly, the class III center curve has a broad main peak, and the peak frequency of the curve it contains has a large variation range which indicates that the vibration of the collection is affected by multiple external excitations and the strong nonlinear changes of the structural parameters of the vibration system. What’s more, the Class IV center curve has multiple peaks in the mid-high frequency band, indicating intermittent mid-high frequency or impact excitation components contained in the vibration.

Statistics are performed on each valid classification to obtain the distribution of the set of curves around the centerline as shown in Figure 11 (The third valid class was taken as an example). And the first-order adjacent conditional probability between each valid category was obtained as shown in Table 1 (the first, third, fifth, and seventh valid classifications was taken as an example).
Figure 11. Distribution of each curve in the third effective classification around the cluster center

Table 1. First-order adjacent conditional probability between valid classifications (partial)

|   | 1   | 3   | 5   | 7   |
|---|-----|-----|-----|-----|
| 1 | 0.2414 | 0.2414 | 0.0345 | 0   |
| 3 | 0.1176 | 0.3529 | 0.1176 | 0   |
| 5 | 0   | 0   | 0.1667 | 0.1667 |
| 7 | 0.4 | 0   | 0   | 0   |

It can be seen from Table 1 that the effective classifications are not uniformly distributed randomly, but tend to be more obvious in groups and continuously appear, thus showing obvious frequency domain non-stationary characteristics. According to the above reconstruction method, to begin with, the category of the reconstructed column vector is sequentially specified by the first-order adjacent probability described above. According to the full probability formula, when the number of reconstructed column vectors is large enough, the overall probability of each class of reconstructed column vectors will theoretically be consistent with the original signal, which proves the feasibility of the method.

This paper selects 10 times the original signal length for reconstruction. The obtained reconstructed signal and the original signal normalized column vector are compared with the normalized column vector image as shown in Figure 12 and Figure 13.

As can be seen from the two figures, the reconstructed signal is basically consistent with the normalized column vector image of the original signal and the probability of each effective classification. It is verified that the reconstruction of the normalized column vector by category and scatter feature can effectively simulate the frequency domain non-stationary features in the wheel equipment vibration.
As shown in Figure 14(a), the generalized energy sequence of the original acquisition spectrum. When the original signal is stable, the generalized energy sequence can be considered as a random sequence satisfying a certain distribution (there is a lognormal distribution). The reconstructed generalized energy sequence generated according to the distribution is as shown in Figure 14(b), and the probability density distribution of the generalized energy sequence of them is as shown in Figure 15. By assigning the reconstructed generalized energy sequence to the reconstructed normalized vector shown in Figure 14(b), the reconstructed wavelet packet coefficient image was obtained as shown in Figure 16.

Based on the wavelet packet reconstruction shown in equation (2), the reconstructed wavelet coefficient matrix is reconstructed by wavelet packet to obtain the reconstructed vibration spectrum. The comparison of the time domain waveform of the reconstructed spectrum and the original spectrum is shown in Figures 17, and the comparison of the overall power spectral density and the amplitude probability density of the two is shown in Figure 18 and Figure 19.
Figure 18. Power spectral density

Figure 19. Amplitude probability density distribution

In the above three figures, it can be found that the reconstructed spectrum obtained by this method has similar non-stationary characteristics with the original acquisition spectrum. Moreover, it also has a high consistency with the original acquisition spectrum in the time domain waveform, the overall power spectral density and the amplitude probability density. In addition, according to the nature of the DB wavelet packet, it is possible to make a flexible choice between the smoothness continuity and the power spectrum consistency of the original acquisition spectrum by reasonably selecting the order of the vanishing moment of the wavelet packet: for vibration spectra with more impact high amplitude excitation and poor smoothness, a wavelet packets with lower vanishing moment order was supposed to selected; on the contrary, for a relatively gentle vibration spectrum, a wavelet packet with a high vanishing moment was supposed to be selected.

5. Conclusion

In this paper, a non-stationary road spectrum reconstruction method is proposed. The harsh environment in which the vehicle is driving was fully considered in this method, which is based on FCM clustering wavelet packet coefficient matrix reconstruction. It was verified that the reconstruction spectrum edited by this method can accurately describe the characteristics of the driving road of the wheeled vehicle and truly reflect the actual vibration response characteristics. It provides a road spectrum input signal with a higher degree of coincidence with the actual road conditions for the road simulation test research of wheeled vehicles, which improves the test accuracy and effect.

Reference

[1] Putra T.E., Abdullah S., Schramm D., et al. The need to generate realistic strain signals at an automotive coil speing for durability simulation leading to fatigue life assessment[J]. Mechanical Systems and Signal Processing. 2017, 94:432-447.

[2] Rajendiran S, Lakshmi P. Simulation of PID and fuzzy logic controller for integrated seat suspension of a quarter car with driver model for different road profiles[J]. Journal of Mechanical Science & Technology, 2016, 30(10):4565-4570.

[3] Deodatis G. Simulation of Ergodic Multivariate Stochastic Processes[J]. Journal of Engineering Mechanics, 1996, 122(8):778-787.

[4] Sun L. Simulation of pavement roughness and IRI based on power spectral density[J]. Mathematics and Computers in Simulation, 2003, 61(2):77-88.

[5] SCHIEHLEN W, HU B. Spectral simulation and shock absorber identification[J]. International Journal of Non-Linear Mechanics, 2003, 38(2):161-171.

[6] Zhu, Yue Feng, Wang, Li. Research on the Simulation of Random Road Excitation in Time-Domain[J]. Applied Mechanics & Materials, 2015, 738-739(6):508-511.

[7] Lu Y, Li Q, Liang S Y. Adaptive prognosis of bearing degradation based on wavelet decomposition assisted ARMA model[C]// IEEE Information Technology, Networking, Electronic & Automation Control Conference. IEEE, 2018.

[8] Bogsjö K. Road profile statistics relevant for vehicle fatigue[D]. Lund, Sweden: Lund University, 2007.

[9] Garcia-Romeu-Martinez M A, Rouillard V. On the Statistical Distribution of Road Vehicle Vibrations[J]. Packaging Technology & Science, 2011, 24(8):451-467.
[10] Rouillard V, Sek M A. Statistical modelling of predicted non-stationary vehicle vibrations [J]. Packaging Technology & Science, 2002, 15(2):93-101.

[11] Rouillard, Vincent. Decomposing pavement surface profiles into a Gaussian sequence [J]. International Journal of Vehicle Systems Modelling and Testing, 2009, 4(4):288.

[12] Wen Y K, Gu P. HHT-BASED SIMULATION OF UNIFORM HAZARD GROUND MOTIONS [J]. Advances in Adaptive Data Analysis, 2009, 01(01):71-87.

[13] Kim J T, Kim C W, Kim T H. Generation of Displacement Signal for Realizing Road Profile using the Accelerometer [J]. Journal of the Science of Food & Agriculture, 2010, 60(2):255-261.

[14] Han S B. Measuring displacement signal with an accelerometer [J]. Journal of Mechanical Science & Technology, 2010, 24(6):1329-1335.

[15] Suh K, Song B, Yoon H. Relative Road Damage Analysis with Driving Modes of a Military Vehicle [J]. 2016, 24(2):225-231.

[16] Huang N.E. Shen Z, Long S.R., et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis [J]. Proceedings A, 1998, 454(1971):903-995.

[17] Haiba M., Varton D.C., Brooks P.C., et al. The development of an optimization algorithm based on fatigue life [J]. International Journal of Fatigue, 2003, 25:299-310.

[18] Daubechies I, Heil C. Ten Lectures on Wavelets [J]. Computers in Physics, 1998, 6(3):1671-1671.

[19] Graps, A. An introduction to wavelets [J]. IEEE Computational Science and Engineering, 1995, 2(2):50-61.

[20] Bezdek, James C. Pattern Recognition with Fuzzy Objective Function Algorithms [J]. Advanced Applications in Pattern Recognition, 1981, 22(1171):203-239.