

Small Amplitude Hunting Instability of High-speed Train Diagnosis Method Based on Modified Ensemble Empirical Mode Decomposition, Shannon Entropy and Least Square Support Vector Machine

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ABSTRACT: To monitor the state of small hunting instability for the train at a high speed, aiming at the problem of mode splitting of ensemble empirical mode decomposition (EEMD), a new methodology which combines modified ensemble empirical mode decomposition (MEEMD), Shannon entropy feature and least squares support vector machine (LSSVM) is presented in this paper to diagnose hunting motion state of high-speed train. Firstly, the vibration signal under 330Km/h~350Km/h is decomposed by MEEMD. Then, calculating the Shannon feature of IMFs and using LSSVM to recognize the hunting motion state. The result shows that the methodology of MEEMD-Shannon features-LSSVM can accurately recognize the unsteady state of hunting motion, the recognition rate is up to 97.78%. Furthermore, the accuracy and computation time are superior to ensemble empirical mode decomposition- support vector machine (EEMD-SVM).

KEYWORD: high-speed train, small hunting, MEEMD, Shannon entropy, diagnose

1 INTRODUCTION

Due to the train wheelset has a taper, when the vehicle rolls along the rail and its speed reaches a critical value, the external self-excitation frequency is close to the natural frequency of the train system and that will contribute to resonance. At this time, coupling forward motion of locomotive wheelset with certain taper will be traversing while shaking around the center line of the track is hunting motion [1, 2]. Hunting instability is a key factor to affect the ride comfort, and possesses safety relevance even leads to derailment [3]. Souza [4] researched hunting instability critical speed by using describing function method. True [5] proposed a calculation method of the non-linear critical velocity. But those studies show that the practical critical speed of hunting instability is significantly differ from the theoretical results because of the track irregularity and yaw damper failures, etc. [6, 7, 8]. Besides, different calculation methods lead to different results of critical speed, and hunting bifurcation is also affects the vehicle stability assessment [9]. Therefore, just using the theoretical analysis method to assess the hunting stability exists severe deficiencies and an on-line monitoring method need to be established urgently.

In order to monitor the hunting stability of high-speed train, Liu et al. [10] built real-time monitoring method of bogie lateral stability by using the Gauss mixture model, Sun et al. [11] used multiple classi-

fication and SVM method to recognize the bogie lateral instability state, in engineering applications, China installed the bogie instability detection device (BIDS) of Japan Kawasaki Heavy industries in CRH2 to monitor the vibration state of bogie frame. In those studies and applications, hunting Instability evaluation criteria is as follows: the peak value of bogie lateral vibration acceleration reaches or exceeds the limit of $8\text{m/s}^2 \sim 10\text{m/s}^2$ (adapting with the design of the steering rack) for more than 6 times (including 6), it is identified that hunting instability [12]. But in actual running process, due to the small displacement perturbation of wheelset, the wheel/rail equivalent taper and creep force decrease easily and that lead to small hunting vibration, at this time the peak value of frame lateral acceleration did not reach or exceed the safety limit value of hunting motion [13,14]. Small amplitude hunting instability state is a symptom of intensive hunting instability and which not only affects the ride comfort but also easily leads to wheel/rail fatigue damage, while existing evaluation methods can not realize the monitoring of this state. To achieve high-speed train running safety, Small hunting state of high-speed train need to be monitored. Meanwhile, it also can provide a method to prevent intensive hunting instability by monitoring small hunting state.

Firstly, when the train runs at a high speed, the vibration signal is usually mixed with the shock signal, because the ensemble empirical mode decompo-

sition (EEMD) has the function of adaptive and suppression of mode mixing [15], it has a unique advantage in processing of this kind of signal, but there remains some shortcomings such as large calculation, time-consuming, modal splitting etc., while the modified ensemble empirical mode decomposition (MEEMD) can solve those problems [16, 17]. Secondly, the time-frequency distribution is highly concentrated when the train hunting instability is occur, Shannon entropy can effectively reflect the degree of signal concentration of time-frequency distribution. Finally, compared with the traditional support vector machine (SVM), least squares support vector machine (LSSVM) is a simplified and fast calculation algorithm [18]. Based on above three reasons, this paper combines the MEEMD, Shannon entropy and LSSVM to identify the small hunting state of high-speed train, the experimental result shows that the proposed method is efficient.

2 REVIEW OF MEEMD AND SHANNON ENTROPY

2.1 Modified Ensemble Empirical Mode Decomposition (MEEMD)

Empirical mode decomposition (EMD) method is widely used in processing non-stationary signals, but there remains many disadvantages such as modal mixing, when the train runs at a high speed, the vibration signal is often mixed with shock signal, using EMD to process the signal will lead to modal mixing. To solve the problem, Huang proposed an improved method, which is adding white noise to the original signal and that decomposed by EMD, namely EEMD, this method can effectively inhibit the modal mixing [15]. But the modal mixing problem cannot be decomposed completely if the amplitude of the added white noise is too low, while it will increase the average amount of calculation if the amplitude is too high, and which will cause the high frequency component of the signal is hard to be decomposed. Besides, the intrinsic mode functions (IMFs) decomposed by EEMD may occur mode splitting problem. In view of this, Zhen et al. [16] proposed a modified EEMD algorithm, which can restrain the mode mixing and solve the mode splitting, and can improve the efficiency of the algorithm, namely MEEMD.

The MEEMD decomposition steps for non-stationary signals are as follows:

1) Adding the white noise signals $n_i(t)$ and $-n_i(t)$ to the original signal $x(t)$ respectively, as

$$\begin{cases} x_i^+(t) = x(t) + a_i n_i(t) \\ x_i^-(t) = x(t) - a_i n_i(t) \end{cases} \quad (1)$$

Where a_i is the amplitude of the white noise signal, and $n_i(t)$ is the white noise signal.

2) In the following, $x_i^+(t)$ and $x_i^-(t)$ are decomposed by EMD respectively, as

$$\begin{cases} x_i^+(t) \xrightarrow{EMD} \sum_{i=1}^n c_i^+(t) + r(t) \\ x_i^-(t) \xrightarrow{EMD} \sum_{i=1}^n c_i^-(t) + r(t) \end{cases} \quad (2)$$

Where $c_i^+(t)$ and $c_i^-(t)$ are IMFs decomposed by EMD respectively.

3) Calculating the average of $c_i^+(t)$ and $c_i^-(t)$, and thus eliminating the residual white noise as much as possible..

$$c_i(t) = 0.5(x_i^+(t) + x_i^-(t)) \quad (3)$$

4) Because $c_i(t)$ is not a standard IMF, and there may be some problems such as mode splitting, which can be called as the pre intrinsic mode function (Pre-IMF), the EMD decomposition of this component as follow:

$$c_i(t) \xrightarrow{EMD} b_i(t) + q_i(t) \quad (4)$$

$$h_k(t) = [q_{k-1}(t) + c_k(t)] \xrightarrow{EMD} d_k(t) + q_k(t) \quad (5)$$

Where $b_i(t)$ is the first standard IMF of $c_i(t)$, and $d_k(t)$ is the residue of the Pro-IMF decomposition, $h_k(t)$ is the k th Pre-IMF, $d_k(t)$ is the first component of $h_k(t)$ decomposition and $k = 2, 3, 4, \dots, m$.

5) As a result, the signal can be expressed as

$$x(t) \xrightarrow{MEEMD} \sum_{l=1}^m d_l(t) + r(t) \quad (6)$$

Where $d_i(t)$ represents the i th IMF, and $r(t)$ is the residue of the signal decomposition.

2.2 Shannon entropy

Shannon entropy is a kind of commonly used information entropy, which can be used as the criteria to judge the uncertainty of a signal. To be specific, a signal can get a larger Shannon entropy value if it is well-regulated. Under normal running state, vibration signals are randomly distributed in the whole frequency range and the information in the signal is uncertain, so that the value of Shannon entropy is small. However, when faults occur, the certainty of the signal in specific frequency band will increase,

so that the value of Shannon entropy in that frequency band becomes relatively large. Therefore, Shannon entropy of the IMFs can reflect the quantity and distribution of the information in vibration signals so well that it can be utilized to characterize the properties of faults [18]. The Shannon entropy of the instantaneous amplitude of IMFs is defined as:

$$S_i = \sum_{t=1}^n |d_i(t)|^2 \log(|d_i(t)|^2) \quad (7)$$

3 A NEW DIAGNOSIS METHOD WHICH COMBINES MEEMD, SHANNON ENTROPY AND LSSVM

High speed train bogie hunting instability occurs when it is in the resonance state, the frequency distribution is more centralized than that of normal running. Vibration signal is decomposed by MEEMD, the envelopes and their means are used to generate a collection of intrinsic mode functions (IMFs). If the IMFs contain hunting faults feature information, the time-frequency distribution will be more centralized, and its Shannon entropy value is smaller. On the contrary, when the components of IMFs contain less fault feature information, the time-frequency distribution is less centralized, and its Shannon entropy value is larger. Therefore, this paper first used MEEMD to decompose the normal, small amplitude hunting and large amplitude hunting signals of the high-speed bogie frame. Then, using the HT to analyze the time-frequency concentration, and calculating the Shannon entropy value of each IMF and constructing the feature matrix. Finally, using Shannon feature to train LSSVM and test the recognition rate of the different three states.

The steps of feature extraction are as follows:

1) Using MEEMD to decompose the healthy, small hunting and large hunting signals respectively and getting the IMFs components.

2) Obtaining the Shannon entropy value of each IMFs, because MEEMD is a principal component analysis method, The main information of the signal is included in the first several IMFs components, according to the actual situation, the first 6 IMFs components was gotten in this paper, $H_{in}, 1 \leq i \leq 6$, n is the number of samples.

3) Constructing a feature vector of the 6 Shannon entropy value.

$$V = [H_{i1}, H_{i2}, \dots, H_{in}]$$

4 EXPERIMENTAL ANALYSIS

4.1 Data acquisition

The bogie frame acceleration data is acquired in a field test between two cities from Beijing to Hangzhou in China. The CRTS II ballastless track and seamless rail are adopted in the whole line, running speed of the train is 320~350km/h and sampling frequency is 2500Hz. The resampling frequency is set to 250Hz according to the Shannon sampling theorem due to the frequency range of hunting is 2~12.07Hz. Band-pass filter the signal after resampling for 2~12.07Hz, and the time domain waveform of the lateral acceleration after filtering is shown in Fig. 1.

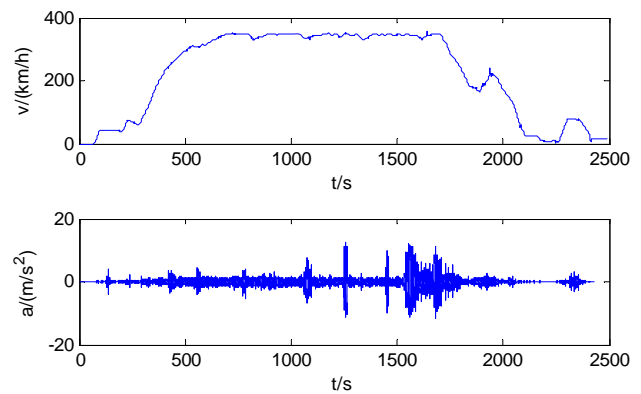


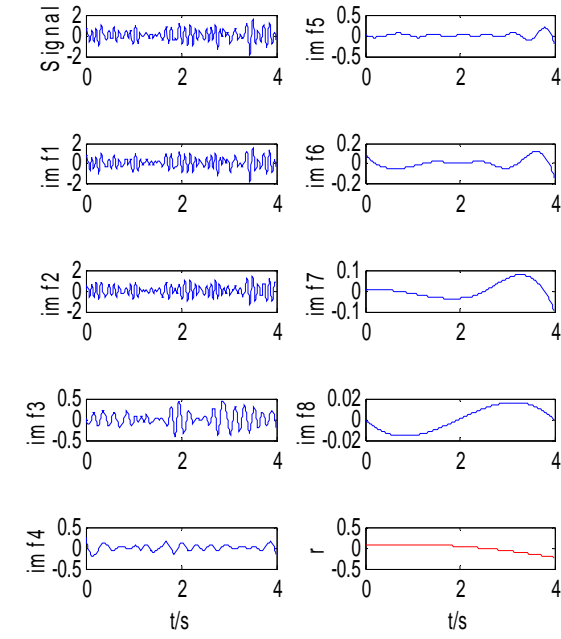
Fig. 1 Time-speed and time- lateral acceleration of bogie frame

According to the literature [4], the healthy driving state is that the amplitude of the lateral acceleration signal of frame is not more than 2m/s², the small hunting state is the part of not reaching or exceeding the safety limit of transverse acceleration signal of framework when the wheel has small displacement perturbation. The hunting with large amplitude is that the part of peak meeting or exceeding 8~10 m/s² more than 6 times (including 6) according to China's railway passenger traffic safety monitoring standard. If high-speed train bogie whether there will be a failure is judged timely according to identify the features of small hunting signal that is very important to ensure the running safety of high speed train.

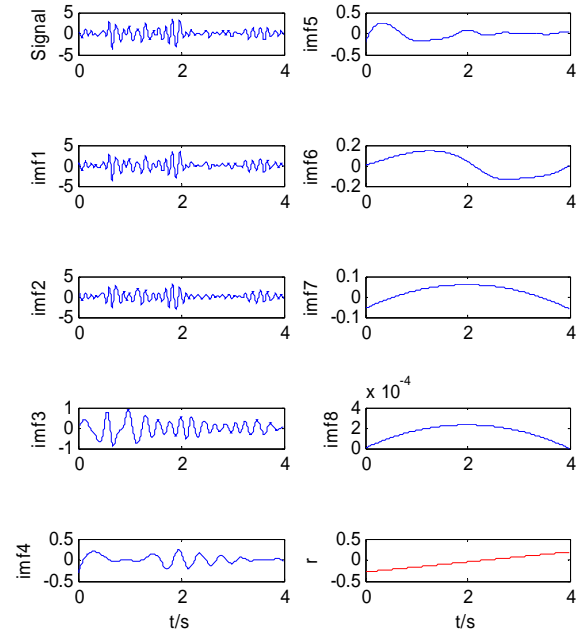
4.2 Signal MEEMD decomposition

The frequency characteristics of the bogie vibration signals are varied greatly in healthy, small hunting and large hunting states, utilizing the MEEMD decomposed IMFs components can reflect different time-frequency concentration and the Shannon entropy feature can effectively reveal the difference between the three states. MEEMD decomposition results in three states are shown in fig. 2. The analysis shows that the frequency of each IMF component

is reduced, and the MEEMD decomposition results of the same scale of the three states are different.



(a) Healthy



(b) Small hunting

(c) large hunting

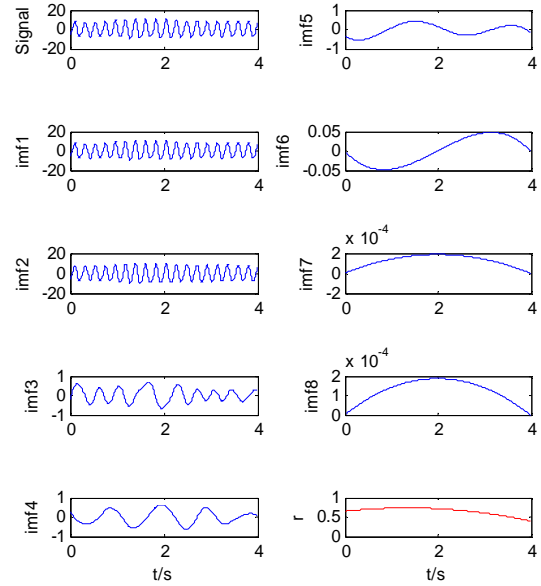
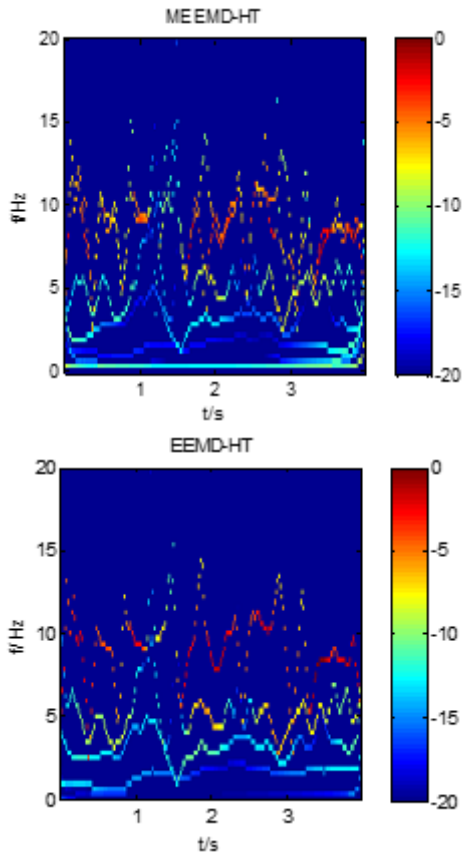


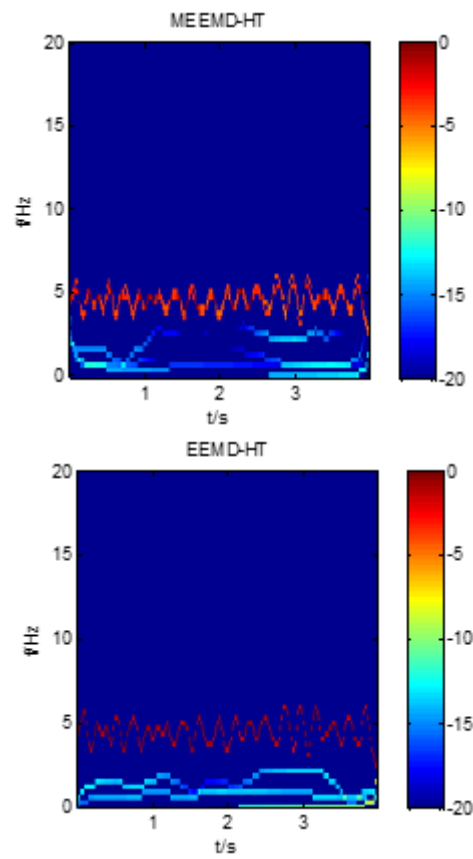
Fig. 2 MEEMD results of vibration signals of various States

4.3 Time-frequency concentration analysis of MEEMD-HT

In order to show the healthy, small hunting and large hunting frequency concentration, using MEEMD to decompose the vibration signals of the three states, and utilizing HT to get the time-frequency-energy distribution spectrum, as shown in fig.3. Comparing with EEMD-HT method, results shows that the bogie speed at 330Km/h ~ 350Km/h, the healthy running frequency distribute in 0 ~ 15Hz, and the energy distribution is mainly concentrated in the range of 4 ~ 12Hz, this is because it is in a state of random vibration when the train under healthy running state, which lead to the frequency and energy distribution is disperse. Under the small hunting oscillation, frequency and energy distribution is more concentrated that that of healthy state, the frequency distribution mainly in 0 ~ 10Hz and the energy distribution is mainly concentrated in the range of 5 ~ 10Hz, time-frequency aggregation is between healthy and large hunting state. Under the large hunting state, frequency, and the energy distribution is highly concentrated, frequency and energy distribution around 5Hz. This is due to the bogie is in the state of resonance. MEEMD-HT spectrum can clearly express the distribute details of energy variety with time and frequency and can clearly show the signal characteristics. The EEMD-HT spectrum, meanwhile, lost many frequency components. In contrast, MEEMD-HT can restrain the mode mixing, solving the modal splitting and is superior to the traditional EEMD-HT method.



(a) Healthy



(c) large hunting

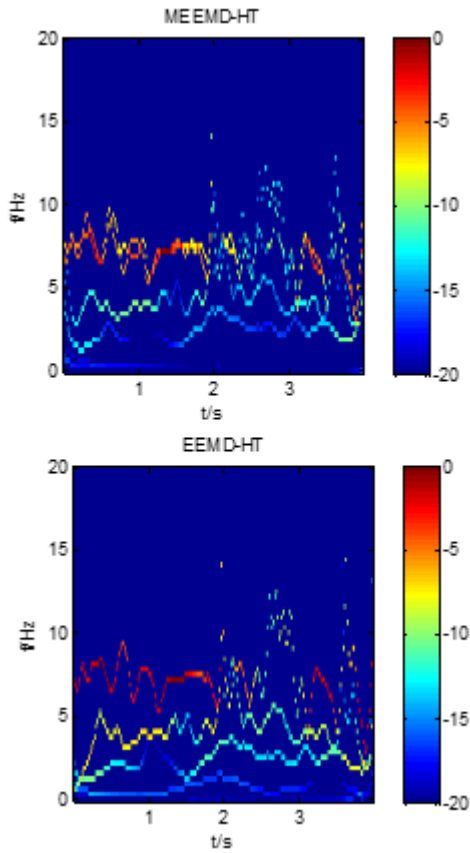
Fig. 3 MEEMD-HT and EEMD-HT results of vibration signals of various States

4.4 MEEMD Shannon entropy feature extraction

From 3.2 and 3.3, the MEEMD-HT spectrums show that the IMFs Shannon entropy of the MEEMD can effectively reflect time-frequency concentration of hunting information, and introducing Sample entropy feature as a contrast. Calculating IMFs Shannon entropy and Sample entropy after getting a series of IMFs decomposed by MEEMD, as shown in tab. 1. Only 2 samples results are given due to space constraints. The analysis shows that the Shannon entropy features of different states are vary obviously, and the same state of the distribution is similar.

4.5 Training LSSVM and the classification effect

The healthy, small hunting and large hunting of bogie frame signals are represented by $t=1$, $t=0$ and $t=-1$ respectively. Extracting Shannon entropy feature and Sample entropy value as the input features of LSSVM respectively and using 90 groups as training samples (30 healthy groups, 30 small hunting groups and 30 large hunting groups). After the completion of the training, using 90 groups (30 healthy groups, 30 small hunting groups and 30 large hunting groups) as the test samples, comparing with MEEMD-SVM, EEMD-SVM and EEMD-LSSVM recognition, as shown is tab. 2. By comparison, the Shannon entropy as the input of LSSVM is better than the Sample entropy, and the recognition rate is 97.78%.



(b) Small hunting

Tab.1 IMFs entropy features of healthy and hunting instability states

Running states	Features	No.	Feature vectors					
			IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
Healthy	Shannon entropy	1	0.7888	0.7756	0.8265	0.8188	0.9178	0.9969
		2	0.7994	0.7670	0.8325	0.8282	0.9299	1
	Sample entropy	1	0.9141	0.8122	0.8962	0.4410	0.1339	0.0020
		2	0.9064	0.7875	0.5829	0.4699	0.1690	0.0004
Small hunting	Shannon entropy	1	0.7056	0.7063	0.6856	0.5635	0.8326	0.8545
		2	0.6988	0.7250	0.6325	0.5243	0.8383	0.8315
	Sample entropy	1	0.9061	0.8314	0.8653	0.4890	0.1116	0.0038
		2	0.8730	0.7225	0.7634	0.4502	0.0932	0.0065
Large hunting	Shannon entropy	1	0.6175	0.7901	0.4950	0.6469	0.8081	0.9561
		2	0.6235	0.7438	0.5208	0.6282	0.7948	0.9561
	Sample entropy	1	0.6196	0.5715	0.3659	0.3025	0.0054	0.0037
		2	0.7495	0.5660	0.3854	0.2946	0.0528	0.0036

Tab 2.Recognition results of LSSVM for healthy and hunting instability states of various features

Features	Output results			Recognition rates
	1	0	-1	
Shannon entropy	30	28	30	97.78%
Sample entropy	28	26	25	87.78%

Tab. 3.Accuracy and computation time of different diagnose methods

Diagnosis methods	Recognition rates	Computation time(s)
MEEMD-LSSVM	97.78%	2.1102
MEEMD-SVM	90.00%	3.9528
EEMD-LSSVM	83.33%	7.5436
EEMD-SVM	76.67%	9.4202

Calculating the computation time of the MEEMD Shannon entropy -LSSVM diagnosis method, comparing with MEEMD-SVM,, EEMD-SVM and EEMD-LSSVM. as shown in tab. 3. Running software: matlab7.11 R2010b, laptops, CPU: Intel Core i3-380M, 2.53GHz, memory: 2GB. Results show that the MEEMD Shannon entropy -LSSVM diagnosis method of high-speed train hunting instability is the best, with highest recognition rates and shortest computational time.

5 SUMMARY

Aiming at the small hunting state of high-speed train, a new methodology which combines modified ensemble empirical mode decomposition (MEEMD), Shannon entropy features and least squares support vector machine (LSSVM) was presented in this paper to diagnose hunting motion state of high-speed train. Conclusions are as follows.

(1)Time-frequency distribution of bogie frame vibration signal is dispersed because the train is under the random state. Under small hunting oscillation, the self-excited frequency close to the hunting frequency, time-frequency distribution is relatively concentrated. The time-frequency distribution is highly concentrated when the train is under the large hunting state because it is in the state of resonance.

(2)MEEMD Shannon entropy -LSSVM method can identify the bogie healthy running, small hunting and large hunting states effectively, the recognition result is superior to that of sample entropy, the accurate rate is higher than the MEEMD-SVM, EEMD-LSSVM, and EEMD-SVM method, and the computing time is shortest.

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