Autonomous Fault Identification Method of Train Axle Bearings based on Ginigram and Squared Envelope Spectrum

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Abstract. Axle box bearings are one of the fundamental components of train, and their failure is the most common cause of machine breakdown. Fault diagnosis can effectively ensure the safe operation of axle bearings. However, the fault diagnosis technology of train axle bearings shares the following issues: (1) In the complex operating environment of the train, the fault features of raw signal are covered by the complex noises. (2) The most fault diagnosis methods need users to interpret the result based on their professional knowledge and visual analysis. To address the above issues, this paper combines the Gini coefficient with the 1/3-binary tree to form the Ginigram, which is used to extract fault component from the raw signal. Then, squared envelope spectrum (SES) of filtered signal is used to obtain a new health indicator (HI), so as to identify the bearing fault location and degree. Finally, by taking the statistical threshold of historical data of healthy bearings, an autonomous method is proposed for bearing fault diagnosis. The experimental results of train axle bearings show that (1) Ginigram is more robust to extract the weak fault signals, compared with classical Kurtogram. (2) HI is more accurate in identifying the fault location and degree, compared with the classical indicator.

Keywords: train axle bearings, autonomous fault identification, Ginigram, SES, HI

1 Introduction

As a key component of the train, bearings are essential to ensure the safe operation of the train. Train axle bearings are often exposed to harsh working environments such as high speeds and heavy loads, which can easily induce fatigue, peeling and wear. Fault diagnosis technology can effectively monitor the health status of the equipment and identify the type of equipment fault, thereby effectively preventing the occurrence of safety accidents [1-2]. The intelligent fault identification method can not only effectively ensure the safe operation of trains, but also help reduce the professional requirements and workload of the fault diagnosis for the users.

Envelope spectrum analysis (EA) is an effective method widely used by the industry [3]. However, when the EA is applied to the engineering site of train axle bearing fault diagnosis, there are two practical problems: (1) The fault characteristics in the raw signal is weak: the operating environment of the train is complex, the fault signals are often covered by strong noise, leading to EA false alarms; (2) Most of the applied fault diagnosis methods still need to analyze the fault manually: The applied method requires manual analysis to determine the fault location and fault degree information, which requires a high level of professional knowledge and work experience for users.

To extract weak fault component from raw signal, Antoni [4] proposed Fast Kurtogram method to calculate Spectral Kurtosis (SK) and then select the frequency band with the best signal-to-noise ratio. However, the Kurtogram method has problems such as too large center frequency selection span and too wide filter frequency bandwidth [5]. Subsequently, Barszcz et al. [6] proposed the Protrugram method to improve the frequency resolution and detection efficiency of SK, but its frequency bandwidth needs to be set based on experience. With the further research, Antoni [7] proposed the Infogram method by introducing Spectral Negentropy; similarly, some scholars have successively proposed the L2/L1 norm [8], Gini coefficient [9] and other statistical indicators, these indicators have achieved better results in the presence of random impulse noise.

Some scholars have proposed automatic diagnosis algorithms to reduce the professional knowledge requirements and workload of users. The idea of automatic diagnosis algorithm is to design indicators to quantify the fault characteristics contained in the envelope spectrum. Borghesani et al [10] proposed the ratio of cyclic content (RCC) indicator to identify the fault location, excessive frequency band range leads to large fluctuations in RCC. Then Smith et al. [11] proposed the indicators of second-order cyclostationarity (ICS2), but it is not sensitive enough to early fault.

To address the issue of the train axle bearing fault diagnosis described in the second paragraph, this paper proposes an automatic signal preprocessing and fault information identification method. Firstly, this paper combines the 1/3-binary tree filter banks and the Gini coefficient to form the Ginigram method. By identifying the optimal demodulation frequency band, the fault features can be effectively extracted from background noise, random impulses and other interference. Then, based on the SES of the preprocessed signal, a new health indicator is proposed to automatically extract the information of the fault location and degree of the bearing from the SES. Finally, the statistical threshold is calculated based on a large number of historical health samples to realize the autonomous identification of bearing fault.

2 Methods

2.1 Data Preprocessing based on Ginigram

This section proposes the Ginigram method to select the optimal filter band to complete the preprocessing of the raw signal, so as to address the issue that the fault signal in the train axle bearing is covered by strong noise.

The Gini coefficient is used as a measure of signal sparseness. For mechanical fault diagnosis, it can not only detect the carrier frequency band with the fault features in the signal, but also has good resistance to random impulse noise [9]. The definition of Gini coefficient is as follows:

$$G(x)=1-2\sum_{i=1}^{L}\frac{x_{(i)}}{\|\vec{x}\|_1}\left(\frac{L-i+0.5}{L}\right) \tag{1}$$

where $\vec{x}=[x_{(1)}\ x_{(2)}\ \cdots x_{(N)}]$ is the vector form of signal with a total length of L and the elements are ordered from smallest to largest. $x_{(i)}$ is the i-th element of $\vec{x}$. $\|\vec{x}\|_1$ is the L1 norm of $\vec{x}$.

The Gini coefficient and the 1/3-binary tree filter-bank are combined to greatly improve the detection efficiency. The details of 1/3-binary tree filter-bank can be found in reference [3]. All the elements in the signal sequence calculated by the Gini coefficient must be positive, to make the signal sequences all positive, this paper calculates the Gini coefficient on the square envelope of the sub-signal generated by the 1/3-binary tree. This method is called Ginigram and its process is as follows:

(1) The raw vibration signal is decomposed into several levels, and a quasi-analytical filter is used to perform low-pass/high-pass filtering to generate a 1/3-binary tree filter bank. To ensure that the total length of the data remains unchanged, the down-sampling operation is implemented for each filtering;
(2) After the signal is decomposed by the 1/3-binary tree, calculate the Gini coefficient of each sub-signal envelope according to formula (1);
(3) Select the optimal frequency band according to the maximum value of the Gini coefficient, The sub-signal $x_{l,h}[k]$ is obtained by band-pass filtering.

The formula for $x_{l,h}[k]$ is as follows:

$$x_{l,h}[k]=x[k]\otimes filter_{l,h}[k] \tag{2}$$

where, $\otimes$ is a convolution operation, $filter_{l,h}[k]$ is a band-pass filter with a filtering frequency band of $[l,h]$.

2.2 Autonomous bearing fault identification

After the signal preprocessing is completed, based on the SES of the preprocessed signal, a new HI indicator is proposed to quantify the fault location and fault degree information contained in the SES.

Firstly, calculate the analytic signal of the preprocessed signal:

$$\tilde{x}_{l,h}[k]=x_{l,h}[k]+j\times hilbert\{x_{l,h}[k]\} \tag{3}$$

where, j is a complex number unit and $hilbert\{\cdot\}$ is the Hilbert transform.

Then, calculate the SES of the analytical signal:

$$SES_{l,h}[\alpha_k]=|DFT\{|\tilde{x}_{l,h}[k]|^2\}|^2=\left|\frac{1}{L}\sum_{k=0}^{L-1}|\tilde{x}_{l,h}[k]|^2 e^{-j2\pi\alpha_k/F_s}\right|^2 \tag{4}$$

where, $DFT\{\cdot\}$ is the discrete Fourier transform， α_k is the cyclic frequency, F_s is the sampling frequency of the signal.

According to the dynamic characteristics of the bearing, the random sliding between the bearing components will cause a few percent error between the fault characteristic frequency and the theoretical value [2], which will cause the fault characteristic identification error. This paper designs a narrow band that takes into account the frequency error. The definition of narrowband is as follows:

$$\begin{cases} B_l(1) = \alpha_{c1} - \mu_i \alpha_{c1}, \quad i = 1 \\ B_l(i) = i \times \alpha_{d1} - \mu_i \alpha_{d1}, i = 2, \cdots, N \end{cases} \tag{5}$$

$$\begin{cases} B_r(1) = \alpha_{c1} + \mu_i \alpha_{c1}, \quad i = 1 \\ B_r(i) = i \times \alpha_{d1} + \mu_i \alpha_{d1}, i = 2, \cdots, N \end{cases} \tag{6}$$

where, α_{c1} is the estimated fault characteristic frequency, α_{d1} is the fault characteristic frequency corresponding to the peak in the first narrowband. μ_i is the error coefficient, set between 5% and 10%. N is the number of harmonics of interest.

Identify the fault peak from the narrowband:

$$m(i) = \max\{SES_{l,h}[\alpha_k]\} \quad \alpha_k \in [B_l(i), B_r(i)] \tag{7}$$

where, $\max\{\cdot\}$ represents the calculation of the maximum value.

After identifying the peaks of the fault features of interest, this paper proposes a new health indicator, the calculation formula is as follows:

$$HI = \frac{\sum_{i=1}^{N} M(i)}{median\{SES_{l,h}[\alpha_k]\}} \quad \alpha_k \in [B_l(i), B_r(i)] \tag{8}$$

where, $median\{\bullet\}$ represents the calculation of the median.

For the fault identification of inner race and rollers, considering the influence of sub-band frequency, two additional left and right *HI* (HI_l and HI_r) must be calculated. There should be at least one prominent peak at the $\pm\alpha_{sub}$ away from α_{di} , α_{sub} is the rotation frequency of the shaft for inner race fault and is the cage fault characteristic frequency for rollers.

To take a final judgment on whether the bearing is faulty, it is necessary to set a healthy threshold. The threshold T is determined by the *HI* value of a large number of healthy samples with the 3 sigma rule of normal distribution: The probability of the *HI* distribution of the healthy bearing in the interval $\left(\bar{X} - 3\sigma, \bar{X} + 3\sigma\right)$ is 0.9973, where $\bar{X}$ is the mean value of the data, σ is the standard deviation of the data, and events whose values fall outside the above range are extremely unlikely events. Because the *HI* value when the bearing is faulty will be much greater than the health state, the $\bar{X} + 3\sigma$ calculated from a large number of *HI* of healthy bearing data is used as the indicator health threshold:

$$T = \bar{X}_{health} + 3\sigma_{health} \tag{9}$$

In practical applications, to determine the fault location of the bearing, the *HI* and *T* of the outer race, inner race and rollers need to be calculated independently. The complete process of the proposed method is shown in Fig. 1.

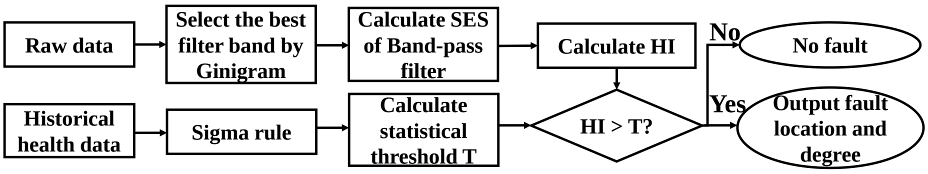

Fig. 1. Complete algorithm flowchart.

3 Experimental validation and results comparison

The naturally worn bearings of the train axle are used in the experiment, the fault of the bearing is shown in Fig. 2. The test rig is shown in Fig. 3, The power of the motor is 75KW, and the speed can reach 1480r/min. With the load device, it can carry out the experiment of the train at different speeds and different working conditions. The vibration acceleration sensor is installed in the 12 o'clock direction (vertical direction) of the axle box. The data collection is completed under the conditions of simulated train running at 90km/h and applying vertical load of 56KN, the sampling frequency is 37268Hz, and the sampling duration of each sample is 1 second. And the shaft rotation frequency is 9.81 Hz, Ball pass frequency on the outer-race (BPFO) is 85.34 Hz, Ball pass frequency on the outer-race (BPFI) is 110.86 Hz, Ball spin frequency (BSF) is 73.01 Hz, Fundamental cage frequency (FTF) is 4.27 Hz.

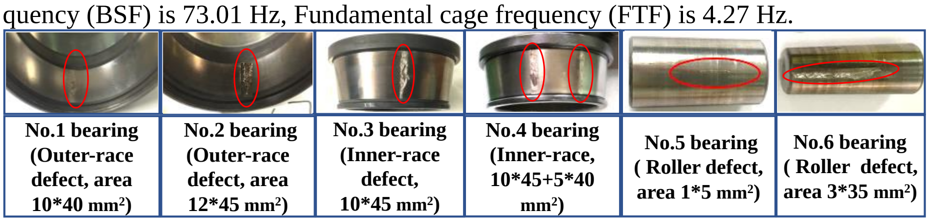

Fig. 2. Faulty bearings.

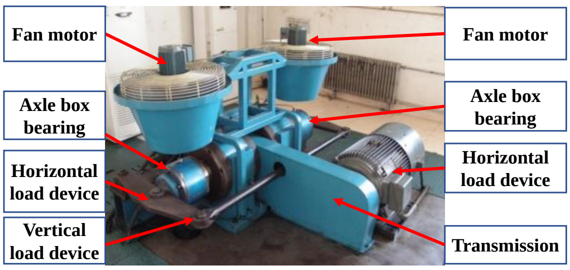

Fig. 3. Train axle test rig.

3.1 Experimental validation of Ginigram

In order to verify the effectiveness of the Ginigram method, an outer race fault case with noise and random impulse interference is selected for comparison and verification. The raw signal is shown in Fig. 4(a), the bearing fault characteristics cannot be directly observed due to strong noise interference.

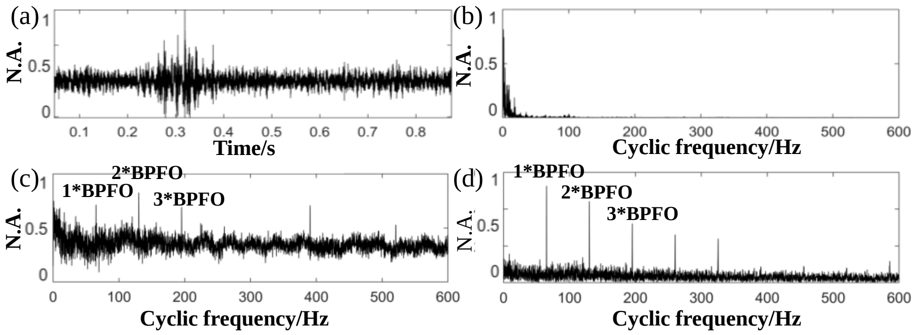

Fig. 4. Result comparison (N.A. means Normalized Amplitude) (a) Raw signal, (b) SES of raw signal, (c) SES of Kurtogram processed signal, (d) SES of Ginigram processed signal.

Compare SES under three conditions: without any preprocess, Kurtogram preprocessing and Ginigram preprocessing. The results are shown in Fig. 4. In Fig. 4(b), the SES of the raw signal cannot observe any fault characteristics; As shown in Fig. 4(c), although the SES of the Kurtogram preprocessed signal contains fault features, the spectral lines of the fault feature peaks are interfered by noise. In Fig. 4(d), the SES of the Ginigram preprocessed signal can clearly show the fault characteristic spectrum and the noise interference is slight. The above results indicates that Ginigram can better extract fault features from the raw signal with strong noise interference.

3.2 Comparison with classical methods

To verify the ability of the HI indicator to identify the faulty part of the bearing, Collect 90 samples for each of the faulty bearings in Fig. 1. The advanced ICS2 indicator in Ref. [10] is used to compare with HI.

Identify the fault location of each group of fault data, and calculate the accuracy rate according to the following rules: The HI is more than threshold T and the corresponding location is considered to be faulty. If the identification result matches the actual fault location and no false alarms occur in other locations, the recognition is accurate; Otherwise, it is regarded as inaccurate.

The accuracy of identifying the fault location of all bearings is shown in Tab. 1, compared with ICS2 indicator, HI has more advantages in accuracy. The most important thing is that HI has a very obvious advantage in the recognition accuracy of weakly faulty bearings with No. 5 rolling elements. It shows that HI is sensitive and effective in identifying weak faults.

Table 1. The accuracy comparison of HI and ICS2 for fault location identification (%).

number	No.1(Outer -race fault)	No.2(Outer -race fault)	No.3(Inner -race fault)	No.4(Inner -race fault)	No.5(Rolle r fault)	No.6(Rolle r fault)
ICS2	94.4	92.2	96.7	91.1	22.2	93.3

HI	**98.9**	**100**	**98.9**	**100**	**48.9**	**98.9**

To verify the ability of the HI indicator to assess the degree of fault, this paper compares the ability of the HI indicator and ICS2 to assess the defect of bearings by using bearings with the same fault location but different defect degree.

The result of the outer race fault is shown in Fig. 5, obviously, both indicators can distinguish between fault and health status. However, the ICS2 can only distinguish part of the fault degree of No. 1 and No. 2 bearings, while the HI can clearly distinguish. The identification result of inner race is similar to the outer race experiment.

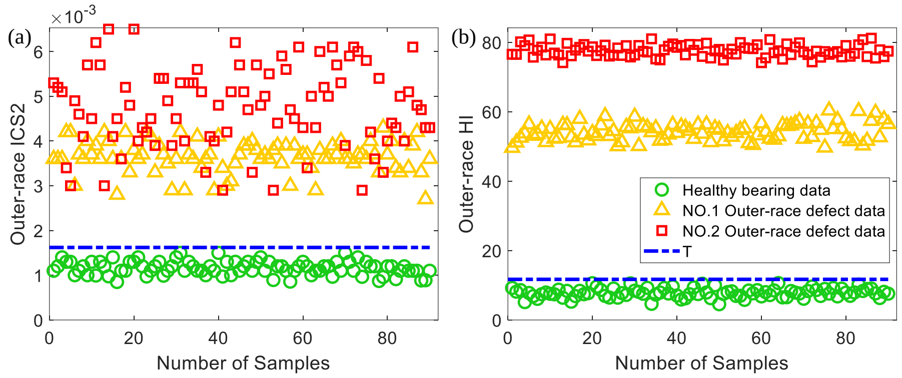

Fig. 5. Comparison of the ability to identify the fault degree of outer race (a) ICS2 (b) HI.

The identification result of the roller fault is shown in Fig. 6. Because the damage of No. 5 bearing is too weak, ICS2 can hardly identify No. 5 bearing, but HI is better than ICS2 in the fault identification of No. 5 bearing, it indicates that HI is more sensitive to weak fault characteristics than ICS2.

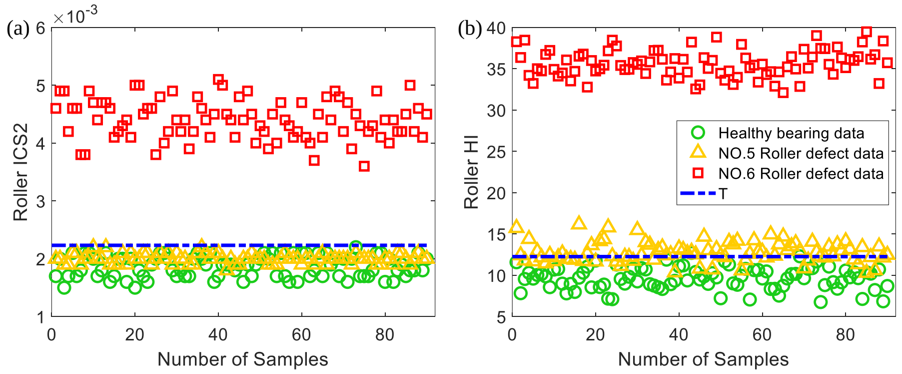

Fig. 6. Comparison of the ability to identify the fault degree of rollers (a) ICS2 (b) HI.

4 Conclusion

This paper proposes a method to automatically identify fault location and degree of the train axle bearing. Firstly, by combining the Gini coefficient with the 1/3-

binary tree to select the optimal filter band, Ginigram is proposed to eliminate the interference of noise on fault diagnosis. Then HI is proposed to automatically identify the fault location and degree information based on SES. Finally, the statistical health threshold is set by counting a large number of historical health data. The experiment data set of train axle test rig is tested to evaluate the performance of the proposed method, the results show that Ginigram is better than Kurtogram in extracting fault signal under complex noise interference, HI is more accurate in fault identification and more sensitive to weak faults than the classic indicator ICS2.

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