# **Rolling Bearing Fault Diagnosis Based on SR and BITD**

Xianyou Zhong, Jiaming Zhao, Li Zhang, Meibao Peng

Hubei Key Laboratory of Hydroelectric Machinery Design & Maintenance, China Three Gorges University, Yichang, 443002, China

zhxy@ctgu.edu.cn, 420222a04sa.cdb@sina.cn, li\_zhang70@qq.com, 13687172531@163.com

**Keywords:** Bearing Fault Diagnosis; B-spline Intrinsic Time-scale Decomposition; Intrinsic Time-scale Decomposition; Stochastic Resonance

**Abstract.** An approach of fault diagnosis of rolling bearing based on B-spline Intrinsic Time-scale Decomposition (BITD) and Stochastic Resonance (SR) was presented. Firstly, SR was used to reduce the noise of the rolling bearing vibration signal, then the bearing vibration signal was decomposed into several Proper Rotations (PRs) by BITD, Finally, the PR containing fault information was analyzed with spectrum, The method was effectively verified by examples of fault diagnosis of rolling bearing.

## Introduction

Rolling bearings is one of the most widely used industrial machinery elements, development of proper monitoring and fault diagnosis methods to prevent malfunctioning is necessary[1]. Rolling element bearings are a vital part of machinery. They often encounter metal-to-metal contacts which result in a consequent wear as compared to fluid bearings. Vibration analysis has been the most widely used technique for condition monitoring of bearings. Faults can be identified by the changes in vibration signature using the signal processing techniques. For rolling bearing fault detection, the time-frequency analysis methods can provide localized information of non-stationary signals in the time domain and frequency domain and has been widely used. The common time-frequency analysis includes Wigner-Wille distribution, wavelet transform[2] and EMD[3]. However, these methods have their own disadvantages, respectively. The difficulty with Wigner-Wille distribution is the severe cross terms. The wavelet transform has been applied to feature extraction for roller bearing vibration signals. However, wavelet bases need to be pre-selected, once the basic wavelet is selected, one will have to use it to analyze all the data, so it lack of self-adaptive. Frei proposed a new method of time-frequency analysis method- intrinsic time-scale decomposition (ITD) [4], ITD signal analysis is adaptive. Frei analyzed biomedical signal by ITD and achieved good results. ITD can be a multi-component signal into some reasonable rotation Proper Rotation (PR) component and a sum of a trend. Compared with EMD, ITD has obvious advantages in terms of computational efficiency. The first component of the signal decomposed by ITD is good, But the second component is distorted. So in the paper, B-spline interpolation to improve the BITD. The BITD is a self-adaptive signal analysis method which is based on the local time scale of the signal and decomposes a multicomponent signal into a number of PRs. Each PR represents a mono-component function versus time. Therefore, the BITD is a powerful signal analysis method for treating non-linear and non-stationary signals.

### The principle of BITD method

The basic decomposition process of BITD method is as follows:

(1) to determine all the local extreme points of the original signal  $X_t$ , the method of BITD is the

same as the ITD, through the formula (1) and (2), to calculate the control points of each baseline  $X_k$ .

$$L_{k+1} = a[X_k + (\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k})(X_{k+2} - X_k)] + (1 - a)X_{k+1} \quad k = 1, 2, \dots M-2$$
(1)

$$LX_{t} = L_{t} = L_{k} + \left(\frac{L_{k+1} - L_{k}}{X_{k+1} - X_{k}}\right)(X_{t} - X_{k}) \qquad t \in (\tau_{k}, \tau_{k+1}]$$
(2)

(2) the sequence endpoint was extended by using mirror symmetry continuation method and get around at both ends of the extreme point, and make k equal to 0 and M, according to the formula (1), reach the value of  $L_1$  and  $L_M$ , and then the B spline function was used to fit all the  $L_k$  to get the baseline signal  $L_1$ .

(3)  $P_1$  was obtained by separating the  $L_1$  from the original signal, if  $P_1$  was a PR component, it would become the first component of the signal  $X_t$ , otherwise it would repeat the above steps as the original signal, cycle k times, until  $P_k$  obtained was a PR component, that  $P_k$  is the first PR component of the signal, that is  $PR_1$ . And a new signal  $r_1$  was got from  $PR_1$  signal separation.

(4) repeat the above steps with the signal  $r_1$  as the original signal, and get the second meeting conditions component of the signal  $X_t$ , that is PR2. Repeated cycle n times, to get n component of the signal  $X_t$  which meet the PR condition, until  $r_n$  was a monotonic function or constant function. In this way, the signal  $X_t$  was decomposed into the sum of n PR components and a monotonic function or constant function. That is:

$$X_{t} = \sum_{i=1}^{n-1} PR_{i}(t) + r_{n}(t)$$
(3)

#### Fault diagnosis of rolling bearing

The experiment rig[5] is shown in Fig.1. It consists of a three phase induction motor, a dynamometer and a torque sensor. The bearings are installed in a motor driven mechanical system. The dynamometer is controlled so that desired torque load levels can be achieved. An accelerometer is attached to the housing with magnetic bases and mounted at the 12 o'clock position at the driven end of the motor housing. The vibration data are acquired by a 16 channel DAT recorder with the 12 K/s sample rate, The faulty bearing type is 6205-2RS, deep groove ball bearing that damaged on an inner race. The single point defect is introduced by the electro-discharge machining. The defect diameter is the 0.07 inch, the speed of the main shaft is 1750 r.p.m., that is, the rotating frequency  $f_r \approx 29.5$  Hz, the characteristic frequency ( $f_{in}$ ) of the inner race fault  $\approx 158$  Hz. Fig.2 shows the vibration acceleration signal of the bearing and its spectrum is shown in Fig. 3. The useful fault information is hidden in the noisy background.



Fig. 1. The schematic diagram of the experimental setup



Fig.3. The spectrum of the signal shown in Fig.2



Fig. 4. The spectrum of the  $PR_1$ 

The Stochastic Resonance is employed to reduce the noise of the bearing vibration signal, and then BITD is employed to decompose the vibration acceleration signal of bearing and 6 *PR*s are obtained. Accordingly, spectrum analysis is applied to the envelope of  $PR_1$  to extract the crucial frequency and the result is shown in Fig. 4. There is one peak value can be observed apparently in the spectrum, it located approximately at 158Hz, and it is identical to the characteristic frequency ( $f_{in}$ ) of the inner race fault, therefore, the fault characteristic frequency of bearing can be clearly observed and the analyzing result is coincidental to the fault type.

#### Conclusion

BITD is a adaptive time-frequency method for nonlinear and non-stationary signals, but the diagnostic effect is affected by noise in the vibration signal, in order to eliminate the bad influence of noise on the diagnostic results, a fault diagnosis method combining BITD and SR was proposed. The method was effectively verified by examples of fault diagnosis.

#### Acknowledgements

I would like to express my gratitude to Education Foundation of Hubei Provincial Department (No. B2015248) and the Natural Basic Scientific Research and Application of Special Projects of Yichang City (No.A15-302-a02), for their useful suggestions and funding support on our thesis.

## References

- [1] Zhong Xianyou, Zhao Chunhua, Chen Baojia.etc. Bearing fault diagnosis method based on morphological filtering and time-delayed autocorrelation and time-frequency slice analysis[J]. Journal of Vibration and Shock, 2014, 33(4): 11-16.
- [2] C. James Li and Jun Ma.Wavelet decomposition of vibration for detection of bearing localized defects, NDT&E International, 1997,30 (3):143-149.
- [3] Li Hui, Zhang Yuping, Zheng Haiqi. Hilbert-Huang transform and marginal spectrum for detection and diagnosis of localized defects in roller bearings [J]. Journal of Mechanical Science and Technology, 2009, 23(2):291-30.
- [4] Mark G. Frei, Ivan Osorio. Intrinsic time-scale decomposition:analysis and real-time filtering of non-stationary signals[J]. Proceedings of the Royal Society, 2007, 463: 321-342.

[5] The case western reserve university bearing data center website. Bearing data center seeded fault

test data [EB/OL]. [2010-11-05]. http://csegroups.case.edu/bearing datacenter/pages/download-data-file.