

# Early fault diagnosis of rolling bearing based on MCKD and auto correlation

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## Abstract

Early fault feature of rolling bearing is very weak and Easily affected by the strongly background noise,So it can not be directly diagnosed.Aiming at solving this problem, maximum correlated kurtosis deconvolution (MCKD) was combined with self correlation analysis and envelope analysis, Early fault diagnosis method for rolling bearing incipient fault was proposed in this paper.firstly, MCKD noise reduction and auto correlation analysis were used in signal, The periodic impact component of the signal is extracted, Then, analysis signal using Envelope, Fault was diagnosed by analyzing the envelope spectrum. The validity of the method in the early fault diagnosis of rolling bearings is verified by analysing simulation signal and engineering test signal.

## Keywords

rolling bearing, Maximum Correlated Kurtosis Deconvolution,self-correlation,Early failure.

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## 1. Introduction

Rolling bearing is one of the most commonly used mechanical components in rotate machine. The running state of the rolling bearing is directly related to the performance of the whole mechanical equipment. Therefore, early fault diagnosis and recognition of rolling bearing has very important realistic meaning.

Vibration signal implied bearing fault information when bearing Early faults occurred, But the periodic impact component caused by failure is very weak,And there still have a strong background noise and other components of the interference, so it increased the difficulty of bearing early fault diagnosis,but also it's a research hotspot in fault diagnosis of bearing. Early bearing fault diagnosis is mainly through a series of noise reduction and other methods to extract the weak impact of the fault component in the vibration signal. In recent years, Aiming at early fault diagnosis, many scholars have done many research. An Guoqing determined the relationship between signal kurtosis and SNR based on the analysis on the characteristics of kurtosis,and designed Kurtosis filter,and extracted the high frequency modulation information of the bearing fault. Wang Hongjun got the early fault sensitivity characteristics based on ensemble average empirical mode decomposition and wavelet packet transform.

This paper combined Auto correlation analysis with maximum correlated kurtosis deconvolution to diagnosis the early fault. maximum correlated kurtosis deconvolution can enhance Impact properties of signal, Autocorrelation analysis can extract the periodic components of the signal, The combination of those can extract the periodic impulse signal and reduce the noise of the signal. Analysis of bearing fault simulation signal and engineering test signal verified the validity of the method in Early fault diagnosis of rolling bearing.

## 2. the principle of maximum correlated kurtosis deconvolution

In order to extract the fault features of the vibration signal, reduce the effect of strong background noise, we make the correlated kurtosis become the maximum by filtering. The correlated kurtosis is proposed based on kurtosis. In comparison with kurtosis, correlated kurtosis is to take advantage of Continuity and periodicity of the impact component in the signal, Fault feature can be characterized through the impact component of signal, so correlated Kurtosis is more suitable for the extraction of fault feature.

Correlated kurtosis is defined as:

$$CK_M = \max_f \frac{\sum_{n=1}^N (\prod_{m=0}^M y_{n-mT})^2}{(\sum_{n=1}^N y_n^2)^{M+1}} \tag{1}$$

$$f = [f_1 \ f_2 \ \dots \ f_L]^2 \tag{2}$$

$y_n$  --- Periodic signal,  $T$  --- cycle of  $y_n$ ,  $f$  --- Filter vector,  $L$  --- Filter Length,  $M$  --- the shift count. In order to select an optimal filter, assuming that:

$$\frac{d}{df_k} CK_M(T) = 0, k = 1, 2, \dots, L \tag{3}$$

The filter is expressed as follows:

$$f = \frac{\|y\|^2}{2\|\beta\|^2} (X_0 X_0^T)^{-1} \sum_{m=0}^M X_{mT} \alpha_m \tag{4}$$

$$X_r = \begin{bmatrix} \mathbf{x}_{1-r} & \mathbf{x}_{2-r} & \mathbf{x}_{3-r} & \dots & \mathbf{x}_{N-r} \\ \mathbf{0} & \mathbf{x}_{1-r} & \mathbf{x}_{2-r} & \dots & \mathbf{x}_{N-1-r} \\ \mathbf{0} & \mathbf{0} & \mathbf{x}_{1-r} & \dots & \mathbf{x}_{N-2-r} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{x}_{N-L-T+1} \end{bmatrix} \tag{5}$$

$$r = [\mathbf{0} \ \mathbf{T} \ \mathbf{2T} \ \dots \ \mathbf{mT}]$$

$$\alpha_m = \begin{bmatrix} y_{1-mT}^{-1} (y_1^2 y_{1-T}^2 \dots y_{1-mT}^2) \\ y_{2-mT}^{-1} (y_2^2 y_{2-T}^2 \dots y_{2-mT}^2) \\ \vdots \\ y_{N-mT}^{-1} (y_N^2 y_{N-T}^2 \dots y_{N-mT}^2) \end{bmatrix} \tag{6}$$

$$\beta = \begin{bmatrix} y_1 y_{1-T} \dots y_{1-mT} \\ y_2 y_{2-T} \dots y_{2-mT} \\ \vdots \\ y_N y_{N-T} \dots y_{N-mT} \end{bmatrix} \tag{7}$$

## 3. autocorrelation analysis

Autocorrelation function describes the degree of correlation of the same signal at different times, it is defined as:

$$R_x(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T x(t)x(t+\tau)dt \tag{8}$$

According to the Autocorrelation Characteristics, The autocorrelation of periodic signals is a periodic signal.

#### 4. Early fault diagnostic process of rolling bearing

In this paper, The method that combined Auto correlation analysis with maximum correlated kurtosis deconvolution for early fault diagnosis of rolling bearing is presented, The diagnostic procedure is as follows:

get the vibration signals. In order to enhance the impact property of the signal, we can handle the signal with maximum correlated kurtosis deconvolution.

In order to extract the periodic impulse components of the signal and reduce the noise interference, we can handle the signal with autocorrelation analysis.

Envelope Spectrum of the signal is drawn. Compare the protuberance frequency of the envelope spectrum with feature frequency of fault.

#### 5. The verification of analog signal

In order to verify the effectiveness of the proposed method, The following analog signal is used to be analyzed, Sampling frequency is 12000Hz, Sampling points are 12000 points, The analog signal is as follows:

$$\begin{aligned} x(t) &= s(t) + n(t) \\ &= \sum_i \exp(-C(t - iT)) \sin(2\pi f_g(t - iT)) + n(t) \end{aligned} \quad (9)$$

$s(t)$  -- Periodic impact component,  $C$  --attenuation coefficient,  $f_g$  -- resonance frequency,  $f$  ---Fault characteristic frequency,  $n(t)$  --- white Gaussian noise.

The Signal-to-Noise Ratio is -8dB after adding noise, The waveform of the shock signal is shown in Figure 1. The waveform of the analog fault signal is shown in figure 2.

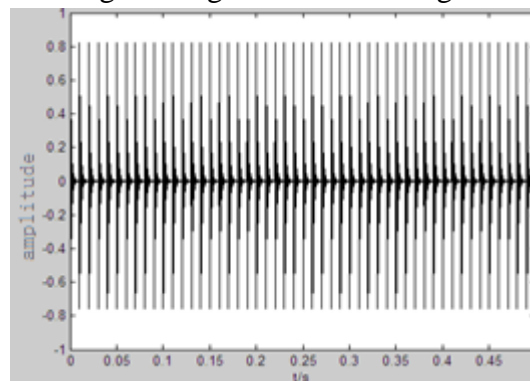


Figure 1 The waveform of the shock signal

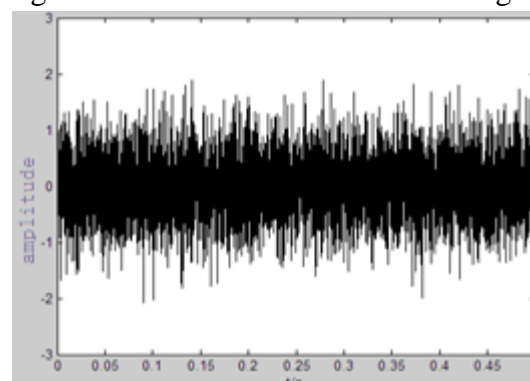


Figure 2 The waveform of the analog fault signal

It can be found that after adding Gauss white noise, the impulse signal is completely submerged by noise, and the law of the signal can not be found in the time domain waveform by comparing the figure 1 to figure 2. The envelope spectrum of analog signals is shown in figure 3, And there is no place where the amplitude of spectral line is particularly prominent.

The analog signal is analyzed by the method proposed in this paper, The analysis result are shown in Figure 4, Fault frequency can be obviously found, So this method can effectively extract the fault frequency from strong noise.

Envelope diagram of fault signal that is processed by MCKD is shown in figure 5, There are several spectral lines in the graph. But it's got nothing to do with fault frequency. Envelope diagram of fault signal that is processed by autocorrelation analysis is shown in figure 6, Although the fault frequency is obvious, but only the fault frequency of the first three frequency spectrum is obvious.

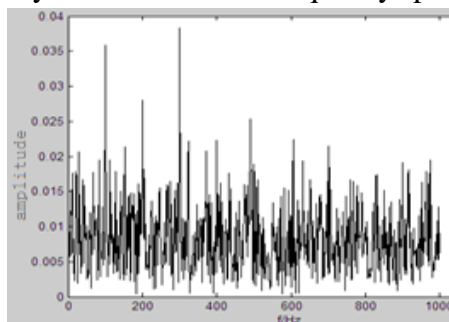


Figure 3 The envelope spectrum of analog signals

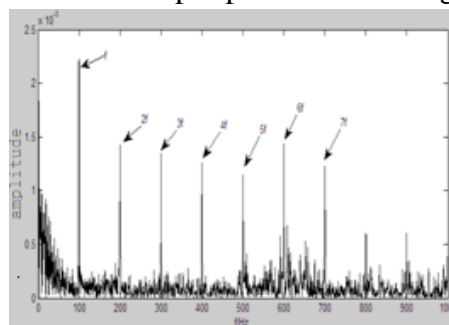


Figure 4 The final result

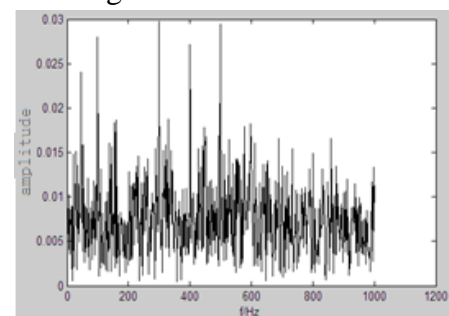


Figure 5 Envelope diagram of fault signal that is processed by MCKD

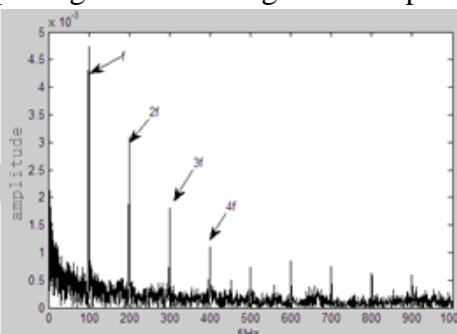


Figure 6 Envelope diagram of fault signal that is processed by autocorrelation analysis

### 6. Case analysis

In this paper, Using fault data of Rolling bearing fault simulation test bench of Electrical engineering laboratory, Case Western Reserve University, USA. In the experiment, there have SKF6205 bearing on the drive end and SKF6203 bearing on the fan end. The local damage of rolling bearing was made by electric spark machining technology, Damage diameters were 0.1778, 0.3556, and 0.5334mm. The fault data of the rolling bearing in the fan end is selected to be analyzed. In order to more close to the real situation, damage diameter of rolling element is 0.1778mm, Diameter of outer ring is 39.9999mm, Diameter of inner ring is 17.0002mm, pitch diameter is 28.4988mm, The ball diameter is 6.7462mm, The number of roller is 8, The contact angle is 0°, The speed of motor shaft is 1750r/min, sampling frequency is 12kHz, According to the structure data, the fault characteristic frequency of the rolling element can be calculated as 116.63Hz.

The waveform of rolling element fault signal that were measured by acceleration sensor on the fan end is shown in figure 7, Impact component of the time domain waveform is not obvious. Envelope spectrum is shown in figure 8, Spectral line is very messy in the envelope spectrum, And there is no place where the amplitude of spectral line is particularly prominent. So extracting the fault characteristic frequency is impossible.

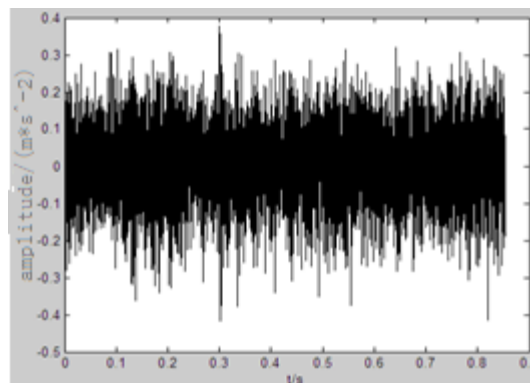


Figure 7 The waveform of rolling element fault signal

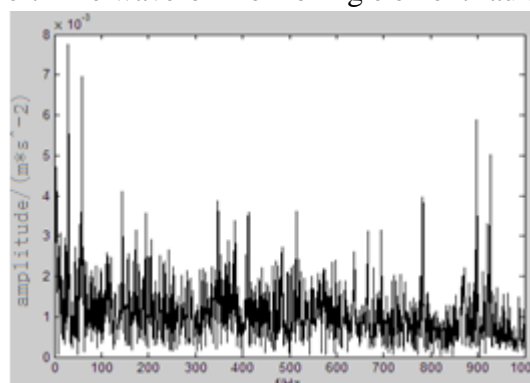


Figure 8 Envelope spectrum of rolling element fault signal

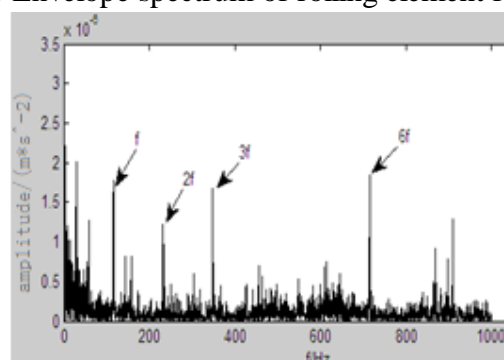


Figure 9 Bearing fault signal is analyzed by the method

Bearing fault signal is analyzed by the method proposed in this paper, the analysis results are shown in Figure 9, amplitude of fault Frequency is prominent. Therefore, the rolling element fault can be diagnosed. The result accords with fact, so the method proposed in this paper can be applied to the early fault diagnosis of rolling bearings.

### Acknowledgements

The vibration signal of rolling bearing is very complex, especially when the rolling bearing happens to early failures, Fault signal is very weak, so early fault diagnosis of rolling bearing is difficult. In this paper, a method that combining MCKD with autocorrelation analysis for early fault diagnosis of rolling bearing is presented. The effectiveness of the method is verified by analog signal and bearing fault signal.

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