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Fault Detection of Spindle Rolling Bearings in CNC Machine Tools Based on Odorless Kalman Filtering Algorithm

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Abstract. Due to the various types of faults in the spindle rolling bearings of CNC machine tools, the accuracy of fault detection is reduced. Therefore, a fault detection method for spindle rolling bearings of CNC machine tools based on odorless Kalman filtering algorithm is proposed. The VB6 vibration signal acquisition analyzer is used to collect the operating data of the spindle rolling bearings of CNC machine tools, and the wavelet analysis method is used to denoise the collected data signals. Based on the denoised rolling bearing operation data, the odorless Kalman filtering algorithm is used to process the spindle operation signal, estimate the status of the rolling bearing in real-time, and compare it with the preset fault standards to achieve online monitoring and judgment of bearing faults. The experimental results show that the proposed method can consistently maintain high fault detection accuracy and shorten fault detection time for different types of faults in rolling bearings.

Keywords. Odorless Kalman filtering algorithm; CNC machine tool equipment; Spindle rolling bearing; Fault diagnosis

1. Introduction

CNC machine tool is one of the very important equipment in the manufacturing industry, and its spindle rolling bearing is the key component of CNC machine tool running stability and workpiece processing accuracy [1]. However, due to the harsh working environment, complex load, long working time and other factors, the spindle rolling bearing is vulnerable to wear, fatigue, defects and other faults, resulting in the deterioration of machine tool performance, workpiece processing quality, and even serious accidents [2]. Timely and accurate detection of spindle rolling bearing faults can avoid problems such as machine tool vibration and workpiece quality decline caused by faults and improve the machining accuracy and stability of machine tools [3]. By effectively monitoring and diagnosing the health status of spindle rolling bearings, signs of failure can be found in advance, and maintenance and maintenance measures can be taken in time to extend the service life of the machine tool. Reasonable detection and maintenance of spindle rolling bearing faults can reduce the downtime caused by equipment faults, improve production efficiency, and reduce maintenance and replacement costs.

Reference [4] proposes a rolling bearing fault detection method based on VMD and developmental networks, which performs variational mode decomposition on the

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original signal of the bearing and reconstructs the original signal. After reconstruction, the modal components of the signal are extracted and inputted into a developmental neural network for iterative training, thereby completing the diagnosis of rolling bearing faults. However, the recognition accuracy of this method has certain shortcomings. Reference [5] proposes a rolling bearing fault diagnosis method based on incremental learning. This method collects vibration data of the main shaft bearing, normalizes the data, inputs it into a convolutional neural network, obtains data features through incremental learning, and detects rolling bearing faults through support vector machines. However, this method requires training and processing of the model, resulting in a longer overall fault detection time. Reference [6] proposes a rolling bearing fault diagnosis method based on VMD optimized by the firefly algorithm. This method uses a bandpass filter to select the optimal parameters of the bearing's operating signal, completes signal denoising processing, and uses the firefly algorithm to optimize the parameters of VMD. Using Hilbert transform to extract the features of fault signals, and completing the detection of rolling bearing faults through optimized VMD. However, this method has the problem of low fault detection accuracy.

In response to the problems in the above rolling bearing fault detection methods, a spindle rolling bearing fault detection method for CNC machine tools based on odorless Kalman filtering is proposed in this study.

2. Signal acquisition and filtering processing of spindle rolling bearings in CNC machine tools

In order to comprehensively analyze the signals of the spindle rolling bearings of CNC machine tools, VB6 vibration signal acquisition analyzer is used to collect the operating signals of the spindle rolling bearings of CNC machine tools. The correlation of VB6 vibration signal acquisition analyzer is shown in Table 1.

Table 1. Parameters of VB6 vibration signal acquisition analyzer

Project	Parameter
Number of acquisition channels	4 channels
Collection range	±10V
Sampling rate	1kHz
Resolution ratio	16 bit
Noise level	<0.1mV
Peak detection sensitivity	0.1g
Data transmission method	USB interface
Data storage method	Real time collection and offline saving

Install a VB6 type vibration signal acquisition analyzer at the front end of the spindle of the CNC machine tool equipment, allowing the CNC machine tool to operate at a constant speed of 800r/min without load [7-8]. Record the operation signal of the spindle rolling bearing of the CNC machine tool equipment, and the signal acquisition result is shown in Figure 1.

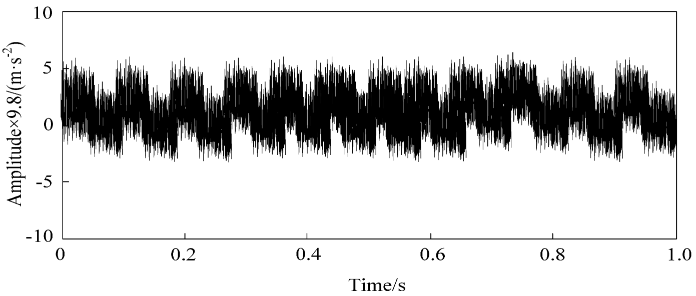

Figure 1. Signal collection results of spindle rolling bearing

After completing the collection of rolling bearing operation data, singular value decomposition method is used for data denoising processing. The Singular Value Decomposition (SVD) method accurately extracts the main features and frequency information from spindle rolling bearing data by decomposing the original data into feature vectors and singular values. This helps to filter and remove noise and interfering components. In addition, the SVD method is suitable for various types of noise and can adaptively weight each component, effectively reducing noise and interference [9]. In addition, the SVD method has flexibility and can control the degree of denoising by adjusting the threshold of singular values.

Let a one-dimensional noisy rolling bearing operation data sequence be $y(t)$, which includes the noise signal $r(t)$, and the expression $y(t)$ can be written as:

$$y(t) = x(t) + r(t) \tag{1}$$

In the formula, $x(t)$ represents a non noisy running data sequence [10].

Using singular value decomposition method to denoise $y(t)$, construct a Hankel matrix for $y(t)$ based on the data sampling sequence number $Y = (y_1, y_2, ..., y_N)$:

$$A = \begin{bmatrix} y_1 & y_2 & \cdots & y_n \\ y_2 & y_3 & \cdots & y_{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_m & y_{m+1} & \cdots & y_{m+n-1} \end{bmatrix} \tag{2}$$

In the formula, $1 < n < N$, $N = m + n - 1$.

Perform singular value decomposition on the noisy matrix $A^{(m\times n)}$ shown in publicity (2):

$$A = USV^{\mathrm{T}} \tag{3}$$

In the formula, S represents the diagonal matrix, and U and V represent the left and right orthogonal matrices. The expression for the diagonal matrix S is:

$$S = \begin{cases} diag(\sigma_1, \sigma_2, ..., \sigma_q, 0) \\ diag(\sigma_1, \sigma_2, ..., \sigma_q, 0)^{\mathrm{T}} \end{cases} \tag{4}$$

In the formula, $\sigma_i (i = 1, 2, ..., q)$ represents the singular value of the noisy matrix $A^{(m\times n)}$.

In order to simplify the calculation of singular value decomposition, formula (3) can be converted into the following form:

$$A = \sum_{i=1}^{q} A_i = \sum_{i=1}^{q} \sigma_i u_i v_i^{\mathrm{T}} \tag{5}$$

In the formula, u_i and v_i represent the i -th column of the left-right orthogonal matrix respectively.

The order p of singular value denoising is selected, and the first p singular values with the greatest correlation with the diagonal matrix S are retained. All other singular values are set to 0 to obtain a new diagonal matrix as follows:

$$S_x = diag(\sigma_1, \sigma_2, ..., \sigma_p, 0..., 0) \tag{6}$$

In the formula, $\sigma_i \neq 0, i = 1, 2, ..., p$.

Through the diagonal matrix and left-right orthogonal matrix, the singular value decomposition is reconstructed by formula (2), and the signal matrix A' is obtained. By restoring the reconstructed signal matrix A' to one-dimensional estimated signal, the rolling bearing operation data signal denoising can be completed.

3. Fault detection of rolling bearing based on Unscented Kalman filter

After the acquisition and de-noising of the running signal of the spindle rolling bearing of CNC machine tools, the unscented Kalman filter is used to detect the fault of the rolling bearing.

Unscented Kalman filter can provide high-precision fault detection results by accurately estimating and predicting system signals. Because the recursive algorithm is used for real-time iterative calculation, unscented Kalman filter has faster calculation speed and real-time performance, and can meet the needs of real-time monitoring. In addition, it also has self adaptability, which can automatically adjust the filter parameters according to the actual observation values, adapt to different systems and environmental changes, and maintain good performance.

The basic form of Unscented Kalman filter can be expressed as:

$$\begin{cases} X_k = f(X_{k-1}) + g(X_{k-1})W_{k-1} \\ Z_k = h(X_k) + j(X_k)V_k \end{cases} \tag{7}$$

In the formula, W_k and V_k represent Gaussian noise, $g(X_{k-1})$ and $j(X_k)$ represent nonlinear system noise and noise transfer matrix.

Since the operation data signal of rolling bearing has been de noised, it is not necessary to take the noise and measurement noise as the state vector, so the unscented Kalman filter with non extended state is used to detect the fault of rolling bearing. In the case of non extended state, the initial state value of Unscented Kalman filter algorithm can be expressed as:

$$\overline{X}_0 = E[X_0], P_0 = E[(X_0 - \overline{X}_0)(X_0 - \overline{X}_0)^{\mathrm{T}}] \tag{8}$$

Calculate the σ -point set and weight generated by unscented Kalman filter:

$$\{X_{k-1}^{(i)}, \omega^{m(i)}, \omega^{c(i)}\}, i = 0, 1, ..., 2n \tag{9}$$

The prediction results of the mean and variance of the state variables of rolling bearings are as follows:

$$\begin{cases} X_{k|k-1}^{(i)} = f(X_{k-1}^{(i)}) \\ \hat{X}_{k|k-1} = \sum_{i=0}^{2n} \omega^{m(i)} X_{k|k-1}^{(i)} \\ P_{X_{k|k-1}} = \sum_{i=0}^{2n} \omega^{c(i)} (X_{k|k-1}^{(i)} - \hat{X}_{k|k-1})(X_{k|k-1}^{(i)} - \hat{X}_{k|k-1})^{\mathrm{T}} \\ + g(\hat{X}_{k-1}) Q_{k-1} g(\hat{X}_{k-1})^{\mathrm{T}} \end{cases} \tag{10}$$

According to the predicted value $\hat{X}_{k|k-1}$ of the rolling bearing obtained by calculation, resample to generate a new set of σ points, which can be expressed as $\chi_{k|k-1}^{(i)}, i = 0,1,...,2n$. Further, the mean value, covariance and cross covariance of the signal measurement of the rolling bearing operation data are predicted and calculated

$$\begin{cases} Z_{k|k-1}^{(i)} = h(\chi_{k|k-1}^{(i)}) \\ \hat{Z}_{k|k-1} = \sum_{i=0}^{2n} \omega^{m(i)} Z_{k|k-1}^{(i)} \\ P_{Z_{k|k-1}} = \sum_{i=0}^{2n} \omega^{c(i)} (Z_{k|k-1}^{(i)} - \hat{Z}_{k|k-1})(Z_{k|k-1}^{(i)} - \hat{Z}_{k|k-1})^{\mathrm{T}} \\ + j(\hat{X}_{k-1}) R_k j(\hat{X}_{k|k-1})^{\mathrm{T}} \\ P_{X_{k|k-1} Z_{k|k-1}} = \sum_{i=0}^{2n} \omega^{c(i)} (\chi_{k|k-1}^{(i)} - \hat{X}_{k|k-1})(Z_{k|k-1}^{(i)} - \hat{Z}_{k|k-1}) \end{cases} \tag{11}$$

Update and calculate the measured values of rolling bearing operation data:

$$\begin{cases} K_k = P_{X_{k|k-1} Z_{k|k-1}} P_{Z_{k|k-1}}^{-1} \\ P_{X_{k|k}} = P_{X_{k|k-1}} - K_k P_{Z_{k|k-1}} K_k^{\mathrm{T}} \\ \hat{X}_{k|k-1} = \hat{X}_{k|k-1} + K_k (Z_k - \hat{Z}_{k|k-1}) \end{cases} \tag{12}$$

The tasteless Kalman filtering algorithm collects and processes the running signals of rolling bearings, estimates the status of bearings in real-time, and compares them with preset fault standards to achieve online monitoring and judgment of bearing faults.

4. Experimentation

In order to test the practical application effect of the proposed method for detecting faults in spindle rolling bearings of CNC machine tools based on odorless Kalman filtering algorithm, the fault detection effect is tested.

This experiment takes the deep groove ball bearing 6406 of the spindle of CNC machine tools as the research object to detect its faults. Deep groove ball bearing 6406 is a rolling bearing with high load-bearing capacity and wide adaptability. Its characteristics include large radial bearing capacity, small friction coefficient, and rolling resistance, and a simple structure that is easy to install and disassemble. In the application of CNC machine tool spindle, deep groove ball bearing 6406 has the advantages of high-speed operation, high load capacity, and long service life, which can stably provide the required operating performance and meet the working requirements of CNC machine tool equipment. The structure of deep groove ball bearing 6406 is shown in Figure 2.

Figure 2. Deep groove ball bearing 6406

The parameters of deep groove ball bearing 6406 are shown in Table 2.

Table 2. Relevant parameters of deep groove ball bearing 6406

Parameter	Numerical value
Outer diameter of outer ring	90mm
Inner diameter of outer ring	71.4
Outer diameter of inner ring	48.6
Inner diameter of inner ring	30
Bearing pitch diameter	60
Rolling body diameter	19.06
Bearing width	23
Number of rolling individuals	6
Contact angle	0°

The types of faults in rolling bearings include fatigue failure, overload failure, friction and wear caused by poor lubrication, bearing looseness or excessive preloading, corrosion and rust, and excessive temperature. For different types of faults, using fault detection accuracy and fault detection time as indicators, this method is compared and validated with reference [4] and reference [5] methods.

The rolling bearing of the spindle of CNC machine tools is one of the key components, and its normal operation has a significant impact on the accuracy, stability, and lifespan of the machine tool. By conducting regular rolling bearing fault detection, potential problems can be identified in advance and maintenance measures can be taken to avoid serious faults and damages. This helps to reduce maintenance costs and downtime, while ensuring the reliable operation of machine equipment. The comparison results of the fault detection accuracy of the three methods are shown in Table 3.

Table 3. Fault detection accuracy

Fault type	**Detection accuracy/%**		
	Proposed method	**Reference [4] method**	**Reference [5] method**
Fatigue failure	95.8	72.8	72.0
Overload failure	95.7	74.5	68.5
Friction fault	93.5	75.6	69.4
Loose or excessively preloaded bearings	96.4	73.0	78.4
Corrosion failure	98.9	74.8	68.5
Rust fault	99.2	76.1	72.6
High-temperature deformation	98.9	72.4	70.8

Based on the comparative analysis of the data in Table 2, it can be clearly seen that this method has significant advantages in fault detection accuracy. For various types of faults, the detection accuracy of this method is significantly higher than that of the methods in reference [4] and [5]. Among them, this method has demonstrated outstanding advantages in fatigue failure, overload failure, friction failure, bearing loosening or excessive preloading, corrosion failure, rust failure, and high-temperature deformation. Specifically, the method proposed in this paper achieves a high level of detection accuracy, such as fatigue failure detection accuracy of 95.8% and overload failure accuracy of 95.7%, while achieving similar good results on other fault types. Therefore, overall, the method proposed in this paper has significant advantages in fault detection accuracy and can provide reliable support for fault diagnosis and maintenance work in related fields.

By verifying the fault detection time, the condition and health level of bearings can be accurately evaluated, and potential faults and defects can be detected early. In this way, corresponding maintenance measures can be taken to repair or replace faulty bearings, avoiding serious faults and damage. This reduces maintenance costs and downtime, while ensuring the reliable operation of machine tools and equipment. The failure and abnormal wear of rolling bearings can cause equipment vibration and increase errors, thereby affecting processing quality and accuracy. By verifying the fault detection time, bearing problems can be detected in a timely manner to avoid processing quality issues caused by faulty bearings. This is crucial for ensuring the stability and consistency of CNC machine tool equipment processing. The fault detection time results of the three methods are shown in Figure 3.

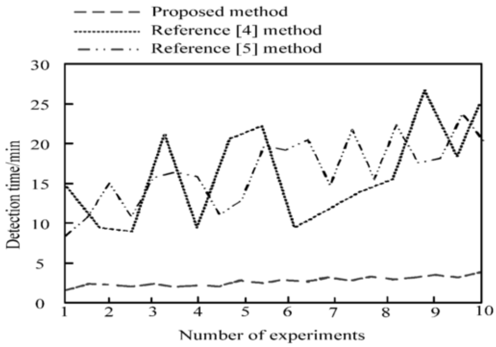

Figure 3. Test time results

From the accuracy results of rolling bearing fault detection shown in Figure 3, it can be seen that under multiple comparative experiments, the fault detection time of the method proposed in this paper is significantly lower than that of the two literature comparison methods. The fault detection time of the method proposed in this paper does not exceed 5 minutes, while the fault detection time of the methods proposed in reference [4] and [5] reaches a maximum of over 20 minutes. Therefore, it indicates that this method can quickly diagnose rolling bearing faults.

5. Conclusion

This study aims to develop a method for detecting faults in spindle rolling bearings of CNC machine tools based on the odorless Kalman filtering algorithm, and to verify the performance of the method from both theoretical and experimental perspectives. This method can accurately detect different types of faults and shorten the fault detection time when detecting faults in the spindle rolling bearings of CNC machine tools. Compared with the detection methods based on VMD and developmental networks, the fault detection accuracy of this method is significantly improved, and the detection accuracy for different types of faults remains above 93%; Compared with the incremental learning based detection method, the fault detection time of this method is significantly shortened, with a maximum detection time of no more than 5 minutes. Therefore, the proposed detection method based on odorless Kalman filtering algorithm can better meet the requirements of fault detection for spindle rolling bearings in CNC machine tools.

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