Research Article

Rolling Bearing Fault Diagnosis Based on Physical Model and One-Class Support Vector Machine

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This paper aims at diagnosing the fault of rolling bearings and establishes the system of dynamics model with the consideration of rolling bearing with nonlinear bearing force, the radial clearance, and other nonlinear factors, using Runge-Kutta such as Hertzian elastic contact force and internal radial clearance, which are solved by the Runge-Kutta method. Using simulated data of the normal state, a self-adaptive alarm method for bearing condition based on one-class support vector machine is proposed. Test samples were diagnosed with a recognition accuracy over 90%. The present method is further applied to the vibration monitoring of rolling bearings. The alarms under the actual abnormal condition meet the demand of bearings monitoring.

1. Introduction

Rolling bearings are widely used in high-end CNC machine tools, aircraft engines, measuring instruments, and other valuable equipment. It plays a key role for the entire work of the host. Carrying out the bearing condition monitoring and fault diagnosis is important to ensure that the equipment is in good working condition. Since fault-prone of early rolling bearing easily exists in most of the bearing work cycle, and most of them are potential problem. Therefore, bearing failure abnormality diagnosis has been a research hotspot [1]. Patil makes a summary about the research Status of rolling bearing fault diagnosis. Compared to fault detection technology, the theory of rolling bearing fault modeling and fault mechanism is particularly inadequate [2]. In recent years, more and more scholars pay attention to the study of rolling bearing fault modeling. Cao established a complex dynamic model about aligning roller bearings, studying the problem of surface damage and preload and radial clearance [3]. Australian scholar Sawalhi [4] established time-varying nonlinear gear integration model, which simulated local spalling and damage fault of bearing. Rafsanjani et al. [5]

established a theory of rolling bearings nonlinear dynamics model, given the mathematical description of the inner ring, outer ring, and rolling element of local damage. Patel et al. [6] established a dynamic model of the deep groove ball bearings, studied on the vibration response of the bearing inner ring and outer ring when it came to single-point and multipoint failure.

About anomaly identification bearing, which is combined with failure mechanism analysis and intelligent diagnosis, this paper first built a physical model of the rolling bearing normal state, and obtain the system response by numerical methods. By dimensionless indicators as characteristic quantities such as kurtosis and peak and building up the bearing diagnosis model based on a class support vector machine, the test bearing diagnosis results show the effectiveness of this method.

2. Physical Model

The structural vibration model of ball bearings can be developed for the rigid rotor system that with the outer ring fixed, the inner ring is equivalent to the concentrated mass.

FIGURE 1: Ball bearing dynamics model.

As Figure 1 shows, bearing kinetic equation can be described as formula (1):

$$\begin{aligned} m\ddot{x} + c\dot{x} + \sum_{j=1}^{N_b} k_b \left[(x \cos \phi_j + y \sin \phi_j) \cos \alpha \right]^{3/2} \cos \phi_j &= F, \\ m\ddot{y} + c\dot{y} + \sum_{j=1}^{N_b} k_b \left[(x \cos \phi_j + y \sin \phi_j) \cos \alpha \right]^{3/2} \sin \phi_j &= 0. \end{aligned} \quad (1)$$

In the above formula, m is the quality of the bearing inner ring, c is the bearing damping, N_b is the number of balls, α is the contact angle (the deep groove ball bearings α is zero), k_b is the coefficient of contact deformation, ϕ_j is the angle of the ball's position, and F is load acting of the bearing outer.

2.1. Contact Deformation Coefficient [7, 8]. Through Hertz theory, the Eschmann had given the expression of elastic deformation of the two-solid-point touching,

$$r_\delta = \frac{3K_b}{\Delta\mu} \left(\frac{(1 - (1/M))^2 \sum \rho}{3E^3} \right)^{1/3}. \quad (2)$$

Here, Δ , K_b , and μ are Hertz coefficients that are determined by the material properties. E , $1/M$, and $\sum \rho$, respectively, are the elastic modulus, Poisson's ratio, and the contact surface curvature. Contact force H is

$$H = \frac{E}{(1 - (1/M^2))} \sqrt{\frac{3r_\delta}{(3K_b/\Delta\mu)^3 \sum \rho}}. \quad (3)$$

Therefore, coefficient of nonlinear deformation of point contacting is

$$K_b = \frac{E}{(1 - (1/M^2))} \sqrt{\frac{3r_\delta}{(3K/\Delta\mu)^3 \sum \rho}}. \quad (4)$$

The calculation methods of curvature about contact surfaces and $\sum \rho$ are given by literature [8]. Thus, once the size of the bearing material is determined, K_b can be obtained by (2)–(4).

2.2. Reliability Verification of Model. In this paper, bearings used FUKATA is calculated in order to verify the correctness of ball bearing model and Table 1 gives the bearing

TABLE 1: Ball bearings parameter table.

Bearings parameter	Numerical
The bearing pitch circle diameter	58.8 mm
Ball diameter	11.9062 mm
Number of balls	8
Clearance	40 μ m
The quality of the rotor (inner ring)	16 kg
External load	58.8 N
Bearing damping	2940 Ns/m

FIGURE 2: Time-domain waveform.

parameters [7]. Because formula (1) has a strong nonlinear state, it has no exact analytical results. This paper has got the system response using the Runge-Kutta numerical checking. Time-domain waveform is shown in Figure 2. The calculated results of FUKATA are shown in Figure 3. On the graph below, upper and lower diagrams, respectively, are bearing a vibration waveform of the horizontal and vertical directions. As seen from the drawing, the calculation results achieved good consistency. The amplitude of the minor difference is due to the material of the bearing and internal structure different parameters.

3. One-Class Support Vector Machine

One-class support vector machine is an unsupervised learning method based on statistical learning theory, having no prior knowledge, structural risk minimization, and so forth. Its purpose is to effectively distinguish the target class samples and other samples. The basic principle of one-class support vector machine is as follows [9]: assume that stems from the same distribution of n -dimensional vector samples $X_1, X_2, X_3, X_4, \dots, X_j \in R^n$, samples are mapped to the high-dimensional feature space F by nonlinear function. Look for a small size region that contains as many sample points in F , which make it separate with the nonclass sample

FIGURE 3: The calculated results of FUKATA.

at maximum intervals. I use the quadratic equation to represent the optimization problem. Quadratic type equation can be expressed as formula (5). In formula (5), ω is Hyperplane normal vector, ρ is the boundary coefficient, $\xi_i \geq 0$ is relaxation factor, l is sample points, and $0 < \nu \leq 1$ is compromise coefficient that determines the distribution volume of the region that contains the sample points of compromise. From the point of view of,

$$\begin{aligned} \min: & \quad \frac{1}{2} \|\omega\|^2 + \frac{1}{\nu l} \sum \xi_i - \rho, \\ \text{s.t.} & \quad (\omega \cdot \phi(x_i)) \geq \rho - \xi_i, \end{aligned} \quad (5)$$

space geometry, sample is projected onto a hypersphere in the equation and the objective of this equation is to find a hyperplane that is quadrature and ω . Its distance from the center of the sphere is $\rho/\|\omega\|$. The function of the equation, the main sample which is away from the center of the hypersphere distributed in this region and was split by hyperplane. In order to ensure the compact structure of the region, a few samples were excluded from outside the distribution area, with the distance from the boundary being ξ_i . Configuring Lagrangian function to solve formula (5), formula (5) is then simplified and we can get formula (6):

$$\begin{aligned} \min: & \quad \frac{1}{2} \sum_{i,j=1}^l \alpha_i \alpha_j K(X_i, X_j), \\ \text{s.t.} & \quad 0 \leq \alpha_i \leq \frac{1}{\nu l} \\ & \quad \sum_{i=1}^l \alpha_i = 1. \end{aligned} \quad (6)$$

In formula (6), α_i is Lagrange coefficient, K is Kernel function, and $K(X_i, X_j)$ is inner product calculation of $\phi(X_i)$ and $\phi(X_j)$ and is denoted $K_{i,j}$. Equation (2) is a typical quadratic programming problem. α_i obtained by solving majority is equal to 0, and only a small portion of A is greater

than 0. The sample corresponding to α_i is called a support vector. Decision function is defined as follows

$$f(x) = \sum_{i=1}^l \alpha_i K(X_i, X_j) - \rho. \quad (7)$$

In formula (7), when $f(x) > 0$, x is located in the distribution of samples within the area; when $f(x) = 0$, x is located at the edge of the distribution area; when $f(x) < 0$, x is located outside the distribution area of the sample. By formula (7), a sample of $\alpha_i = 0$ is ignored in the calculation will. Therefore, the distribution of the target sample in the feature space of the whole only depends on the support vector.

4. Diagnostic Methods of One-Class Support Vector Machine Based on Model

The nature of the fault diagnosis is pattern recognition problem. In this paper, through numerical simulation to build a normal state of the sample, thus eliminate the problem by failure data. However the kurtosis, waveform, margin, peak and skewness of five dimensionless index [8] are the most important factors to a bearing failure, thus take advantage of the dimensionless indicators eigenvectors training one-class support vector machine. Thus, I complete a bearing fault diagnosis. The process of this method is shown in Figure 4.

5. Experimental Study

An experimental study of the vibrated signal in the bearing test, which used to judge the bearing working state. Using SonyEX data acquisition system to get the signal, the sampling frequency is 10 kHz. Figure 5 is a typical test signal time-domain waveform and power spectrum. Table 2 is the anomaly identification result of one-class support vector machine. We can see that correct rate above 90% in Figure 5 and Table 2, which meet the demand of engineering.

FIGURE 4: Class support vector machine diagnosis flowchart.

FIGURE 5: Normal signal waveform and power spectra.

TABLE 2: Abnormal rate of diagnosis of each state.

Bearing condition	Correct rate
Inner ring defect	94.3%
Outer ring defect	90.6%
Ball defects	91.7%

6. Conclusion

This paper presents a model-based ball bearing fault diagnosis method. It is through the use of dynamic models to get the timing of data reconstruction, thus taking advantage of the dimensionless indicators eigenvectors training one-class support vector machine to discover abnormal state. Engineering experiments show the feasibility and effectiveness of this method with the diagnosis rate being up to more than 90%. This results meet the actual monitoring needs of the industrial field.

Conflict of Interests

The authors declare that there is no conflict of interests.

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