Fault Diagnosis Technology of Rolling Bearing in Space Station

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Abstract. With the development of space station engineering, rolling bearings have been widely used in space station. Whether the bearing is healthy or not is related to the safety of the experimental facilities. Fault diagnosis of rolling bearings includes time domain analysis and frequency domain analysis. By analyzing bearing fault information, time-frequency information entropy is more representative as fault feature. Firstly, the vibration signal of acceleration sensor is decomposed by EEMD method, and the intrinsic mode function is obtained. The time-frequency information is obtained by Fourier transform, and the information entropy of the time-frequency information is calculated. Then, the fault feature is self-adaptive dimensionality reduction. Finally, the fault feature is trained by using support vector machine, and the data is tested. The experimental results show that the method can diagnose bearing fault with high accuracy.

1. Introduction

Rotating machinery is widely used in various fields, but the failure of the ground roller bearing will not result in particularly serious effects. The space station is confined space, so the failure of the rotating mechanism can easily lead to a chain reaction and a safety accident. For example, the roller bearing is jammed, which easily causes the motor to start fire. Failure of pump group can lead to pipeline rupture and working fluid outflow. Under microgravity conditions, working fluids will enter electronic devices and cause short circuit fires. Therefore, it is necessary to monitor and diagnose the failure of roller bearing.

The information of equipment state is hidden in rotor vibration signal, which contains information of various abnormality or malfunction of equipment. The vibration signal of roller bearing is nonlinear and unstable, which leads to the traditional method is not applicable[1]. A lot of studies have been carried out by the relevant scholars. Yang Lin carries out complete centralized empirical mode decomposition for diesel engine characteristic information, and carries out fault diagnosis for the inherent component set sample entropy[2]. Hong Jun uses wavelet analysis to decompose centrifuge fault signals. The sub band energy is used as a feature vector to diagnose the centrifuge by fuzzy neural network[3]. Me Torres presents a complete set of empirical mode decomposition methods. In the method here proposed, a particular noise is added at each stage of the decomposition and a unique residue is computed to obtain each mode. The resulting decomposition is complete, with a numerically negligible error[4].

In this paper, the acceleration sensor is used to collect vibration signals, and the EEMD method is used to decompose the signal to get the intrinsic mode function. Fourier transform is used to obtain
time-frequency information according to the obvious components of fault characteristics[5]. For fault characteristics, the cumulative degree of contribution is taken into account to reduce dimensionality. Finally, the fault feature is trained by support vector machine and tested with data. The experimental results prove that the accuracy is higher and a smaller number of filtering iterations are needed.

2. Fault Feature Extraction And Svm Principle

2.1 Vibration mechanism of rolling bearing
Rolling bearings are composed of four parts: inner ring, outer ring, rolling element and cage. When rolling bearings are running, the inner ring usually rotates with the shaft, and the outer ring is fixed with the bearing seat or the machine base. The vibration mechanism of rolling bearing is the result of internal and external factors, which causes the shaft to rotate under the influence of a certain structure and load, and generates excitation to the whole vibration system, so that the system appears vibration.

![Mechanism of Bearing Vibration System](image)

Fig. 1. Mechanism of Bearing Vibration System

In fault diagnosis of bearings, vibration signals need to be collected by sensors. Wire sensors are usually placed on the box near the bearing seat or bearing seat. The signals obtained are comprehensive signals produced by internal and external factors. In this vibration signal, the key point is the vibration caused by operation failure. Bearings need to be pre-tightened when assembling. Because the pre-tightening force can not be measured every time, the pre-tightening force will cause the bearing stiffness to change and lead to the bearing vibration. When the rolling bearing runs steadily at a fixed speed, the vibration has definite and regular characteristics. The surface roughness, shape and position errors formed in the manufacturing process of bearings and the different assembly errors in the assembly process form exciting force, which makes the bearing system vibrate. The vibration generated by the bearing system also contains many frequencies and strong randomness[6].

Any rolling bearing is always accompanied by wear and tear during its operation, which leads to structural change and vibration transformation, and is a kind of deepening fault. The vibration of the bearing surface after wear is stronger than that under normal conditions, but the vibration between them has the same properties, which are irregular and highly random.

The basic characteristics of bearing vibration caused by surface damage faults are as follows: when the bearing rotates through the damaged point of the fault, a sudden change of impulse force will be formed. Because this force is a bandwidth signal, it will cover up the high frequency natural frequency of the bearing system, trigger resonance and cause impact vibration. Surface damage faults can be classified into two categories according to the impact components: one is that the rolling body rotates continuously through the faulty working surface, causing impact to form low-frequency vibration, the other is that impact causes inherent vibration of bearing parts[7].
The first kind of surface damage fault is the low frequency vibration caused by the impact of the damage point. The period can be determined by the rotating speed of the bearing and the shape and size parameters of the bearing. This vibration frequency is called fault frequency. Spectrum analysis method is by observing bearing frequency. Whether fault frequency is included in the spectrum can be used to analyze whether bearing failures occur, and then the fault type can be determined according to the magnitude of the spectrum value.

The theoretical characteristic frequencies (in which the outer ring is fixed and the inner ring rotates) of single point damage of each component of rolling bearing are calculated as follows:

**Outer ring fault characteristic frequency:**
\[
\frac{n}{60} \times 0.5 \times z \times \left(1 - \frac{d}{D} \times \cos \alpha \right)
\]

**Inner ring fault characteristic frequency:**
\[
\frac{n}{60} \times 0.5 \times z \times \left(1 + \frac{d}{D} \times \cos \alpha \right)
\]

**Roller fault characteristic frequency:**
\[
\frac{n}{60} \times 0.5 \times \frac{D}{d} \times \left(1 - \left(\frac{d}{D} \right)^2 \times \cos^2 \alpha \right)
\]

**Characteristic frequency of cage failure:**
\[
\frac{n}{60} \times 0.5 \times \left(1 - \frac{d}{D} \times \cos \alpha \right)
\]

\( n \) is the speed of bearing. \( z \) is the number of rollers. \( d \) is the diameter of the rolling element. \( D \) is the bearing pitch diameter. \( \alpha \) is the contact angle of rolling element.

Because the impact makes the whole bearing system produce high-frequency natural vibration, because each object has its natural frequency, the high-frequency natural vibration of the whole bearing system includes many frequency components, including not only the natural vibration of the rolling body, the natural vibration of the radial bending of the bearing ring, but also the natural vibration of the sensor which collects vibration signals. The most easily observed is the inherent vibration of the inner and outer rings.

### 2.2 Support Vector Machine

The error rate of learning machine on test data (i.e. generalization error rate) is bounded by the sum of training error rate and a term dependent on the dimension; in the case of separable mode, the value of support vector machine for the former term is zero and the second term is minimized. Therefore, although SVM does not use the domain knowledge of the problem, it can still provide good generalization performance in pattern classification. This attribute is unique to SVM. The idea is as follows: the input vector \( x \) is mapped to a high-dimensional feature space \( Z \) by some pre-selected non-linear mapping, in which the optimal classification hyperplane is constructed to maximize the separation boundaries between positive and negative samples. Conceptually, support vectors are those data points closest to the decision plane, which determine the location of the optimal classification hyperplane.

Paired taxonomy is to construct a classifier \( f_{ij} (i \neq j) \) with two different categories of samples. In this way, all the matching combinations can be achieved to obtain the number of \( C_k^2 = k(k-1)/2 \) sub classifiers. Solving the following two classification problems for class \( i \) and class \( j \).

\[
\begin{align*}
\min & \quad \frac{1}{2} \| w_{ij} \|^2 + C \sum_{i,j} \xi_{ij}^+ \\
\text{s.t.} & \quad \left[ (w_{ij}^T x_i) + b_{ij} \right] - 1 + \xi_{ij}^+ \geq 0
\end{align*}
\]
When the sample X of unknown class attributes is tested, the $C^k_1$ sub classifier is used to identify the attribute of the sample.

3. Fault Feature Extraction

3.1 Acquisition of Vibration Information

At present, most of the vibration signals are collected by accelerometers. Short-period signal acquisition can be fixed with tape or adhesive. The disadvantage of fixed mode is that it is easy to fall off under high frequency energy vibration, and noise error cannot be avoided. In the long period signal acquisition, the acceleration sensor can be fixed by screw near the centrifuge. In order to prevent the screw from loosening, special glue is used to fix the screw. The accelerometer will form a vibration system with the rotating vibrator. Low noise coaxial cable is used for information transmission between accelerometer and acquisition instrument. It not only collects vibration information of sensors under normal working conditions, but also collects vibration information under different fault conditions. The sampling frequency of the accelerometer is 10.2 kHz.

3.2 Processing of Vibration Information

For the input signal, all extreme points. The upper and lower envelopes of $X(t)$ are obtained by fitting the maxima and minima with cubic spline function. The mean of the upper and lower envelopes is subtracted from the original data sequence. Usually, the curve does not satisfy the conditions of IMF, so we need to repeat the above steps to process iteratively. The iteration stopping criterion given by Huang is that SD is the threshold value of screening, and generally takes the value of 0.2-0.3. If SD is less than this threshold value, the screening iteration will end. The $S_n(t)$ obtained after n iterations satisfying the stopping criterion is the effective IMF, and the remaining signals enter the next screening process. After many times of screening, the original data sequence is decomposed into a set of IMF components and a residual. The IMF obtained is stationary. The results obtained by Hilbert transform can well analyze the non-linear and non-stationary signals. The six components on the front of a fault are shown in Figure 1.

![Intrinsic modal function](image)

**Fig. 2.** Intrinsic modal function

Short-time Fourier Transform defines a very useful class of time and frequency distributions, which specifies the complex magnitude of any signal changing with time and frequency. In fact, the process of calculating short-time Fourier Transform is to divide a longer time signal into shorter segments of the same length, and calculate Fourier changes in each shorter segment. In other words, Fourier spectrum. A function can be multiplied by a window function that is not zero for only a period of time before one-dimensional Fourier transform. Then the window function is moved along the time axis, and a series of Fourier transform results are arranged to form a two-dimensional representation. The spectrogram of the fifth-order intrinsic mode function corresponding to a failure mode of a roller bearing is shown in Figure 4.
The energy of the signal varies at different frequencies during sampling under different fault modes. In order to quantitatively describe this difference, information entropy is introduced into the calculation.

### 4. Reduction dimension and classification training of fault features

#### 4.1 Reducing dimension by principal component analysis

In order to improve the aggregation degree of fault features and reduce the number of iterations, the dimension of fault features is reduced by principal component analysis. In order to reduce the influence of fault feature dimension, the fault feature matrix is normalized and the eigenvalues and eigenvectors of fault feature are obtained. The cumulative sum of eigenvalues is the cumulative contribution degree, which is usually used to represent the fitting degree of fault features. The larger the fitting degree is, the greater the cumulative contribution value is. However, the more features are selected, the more iterations are calculated, and the longer the calculation time is. Usually the cumulative contribution is not less than 85%. PCA function is used to call in Matlab. The data clustering analysis shows that the two-dimensional fault feature can meet the clustering requirements, so the fault feature is simplified to two-dimensional. The scatter clustering graph of two-dimensional features is shown in Fig. 5.

#### 4.2 Data training and testing

The extracted fault features are divided into training data and test data. The first four groups of fault characteristics corresponding to each fault mode are used as training data and the last four groups as test data. Accuracy of training data used in training model. Finally, the trained classifier model is used to identify the test data fault label. Number 1 stands for normal operation, number 2 for inner ring fault,
number 3 for outer ring fault, number 4 for roller fault, number 5 for mixed fault, and finally, fault label identification for test data. The classification results of the test data are shown in Figure 5.

Fig. 5. The classification results of the test samples

In this paper, the blue circle represents the training fault category, that is, the actual fault category. The training fault type is consistent with the actual fault type. The black cross sign indicates the type of fault diagnosed by the model. After diagnosis, the fault category label is almost identical with the actual fault mode, with an accuracy of 90%. As shown in Fig. 5, the centrifuge fault diagnosis technology has high accuracy. Because of dimension reduction measures, the calculation amount is small and the classification effect is good.

5. conclusion

In this paper, the bearing fault diagnosis method is analyzed, and the time-frequency information entropy is used to judge the fault synthetically. The fault information contained in the acceleration sensor data is separated, extracted, entropy and reasonable dimension reduction, and the final fault characteristics are obtained. The experimental results show that the method has high accuracy and can complete fault classification

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