Research on Intelligent Diagnosis Method of Rolling Bearing Fault Based on Machine Learning

Sun Jianyan, Li Lin, Zeng Weijia
Information Management and System Department, Dalian University of Science and Technology
879527755@qq.com

Abstract: In order to solve the problem of poor intelligent diagnosis results of bearing faults, an intelligent diagnosis method of rolling bearing faults based on machine learning is proposed. Through extracting the characteristics of common fault parameters of rolling bearings, the comparative values of bearing fault diagnosis are obtained. In order to ensure the stable operation of the bearings, a machine-learning rolling bearing diagnosis platform is designed for the acceptable deviation values in the standard operating parameters of the bearings, so as to carry out fault diagnosis and feedback control processing on the operating parameters of the bearings in time, thus realizing intelligent diagnosis of rolling bearings faults. Finally, the experiment proves that the intelligent diagnosis method of rolling bearing fault based on machine learning is obviously improved compared with the traditional method.

1. Introduction
At present, there are many mechanical equipment, technology is more and more developed, mechanical equipment products are more and more advanced, one of the mechanical parts of the bearing is very easy to problem parts, for bearing damage can be detected by hearing, but usually at this time the bearing must be replaced immediately. Therefore, a better method, such as using an electronic monitor for diagnosis, breaks the running condition of the bearing in advance[1]. This method uses advanced instruments to more accurately estimate the bearing condition, and judges the fault condition of the rolling bearing by collecting the sharp squeaking noise audio during the running process of the bearing. This method has higher practicability and can rapidly diagnose the existing fault as soon as possible, but the disadvantage in the United States is that it is less forward-looking and can only diagnose the known fault. The KNF-based fault diagnosis method detects and verifies the rotation speed of the bearing according to the dent vibration condition on the outer race track of the bearing[2]. The method can diagnose the fault more accurately, effectively judge the fault area, but its practicability is relatively lower than that of the electronic monitor diagnosis method, while the PID-based fault diagnosis method has higher practicability and accuracy. Through calculating the running track and standard value of the bearing, the standard parameters are obtained, and the actual running parameters are collected to judge its running fault. At present, this method has been widely used in the production and manufacture of related industrial equipment[3]. However, due to the relatively complex PID algorithm, problems such as calculation errors are easily encountered in the fault diagnosis process, resulting in inaccurate diagnosis structure. Therefore, an intelligent fault diagnosis method for rolling bearings based on machine learning is proposed in order to optimize and improve the traditional method.
2. Intelligent Diagnosis Method of Rolling Bearing Fault

2.1 Fault Feature Extraction of Rolling Bearing

The common faults in the running process of rolling bearings are studied and the fault characteristic parameters are obtained. The research found that the bearing failure includes the inner and outer rings of the bearing and the surface fatigue damage[4]. Under the repeated load, the bearing is prone to poor lubrication, thus causing the bearing fatigue failure. Assuming that the bearing is a rigid body, regardless of deformation, the damage vibration frequency of the bearing can be obtained:

(1) when the inner ring has a damage, the failure frequency is:

\[ f_1 = \frac{1}{2} f_r \cdot n \left( 1 + \frac{d}{D} \cos \theta \right) \quad (1) \]

(2) when the outer ring has a damage, the failure frequency is:

\[ f_2 = \frac{1}{2} f_r \cdot n \left( 1 - \frac{d}{D} \cos \theta \right) \quad (2) \]

(3) when the roller has a damage, the failure frequency is:

\[ f_3 = f_r \cdot \frac{d}{D} \left( 1 - \frac{d^2}{D^2} \cos \theta \right) \quad (3) \]

Where: \( f_r \) represents the inner ring speed frequency; \( D \) is the diameter of the roller; \( D \) is the diameter of the bearing section circle; \( \theta \) is the rotation angle; \( N \) is the number of rollers[5]. According to the analysis results of bearing vibration characteristics, the fault is detected and diagnosed, and the fault information is accurately obtained. The basic process is as follows:

1. to find the source of the fault;
2. to determine the fault location, size, type and reason;
3. check the fault degree;
4. forecasting the fault development trend;
5. Make processing decisions on the detection and diagnosis results.

According to the above process, the fault information of the rolling bearing is accurately detected[6]. On the premise that the operating parameters of the bearing remain unchanged, the fault operation state is close to the normal operation state through fault detection and diagnosis results. Let the dynamic equation under normal operation state be:

\[ Z(x) = f_{x+\alpha} : A\alpha(x) + B\beta(x) \]

\[ W(x) = f_{x+\alpha} : C\alpha(x) \quad (4) \]

Among them, \( \alpha(x) \) indicates a state vector; \( W(x) \) represents a measurement vector; \( \beta(x) \) represents a control vector; \( A, B, C \) are parameters. Use the state feedback shown in the figure below to improve the compensation capability for rolling bearing fault detection.

![Fig. 1 fault compensation for rolling bearing operation state feedback](image)

On this basis, the closed-loop feedback dynamic equation is optimized and can be recorded as follows:
Among them: 

\[ v(x) = \beta(x) - R\alpha(x) \]  \hspace{1cm} (5) 

In the same way, the dynamic equation of rolling bearing under fault operation can be recorded as follows:

\[ Z_i(x) = (A_i - B_iR)\alpha_i(x) + B_iV_i(x) \]  \hspace{1cm} (6) 

In order to make the performance close to the normal performance, the following formula (7) shall be followed for the operation of fault detection:

\[ A - BR = AZ_i(x) - BRW_i(x) \]  \hspace{1cm} (7) 

According to the above formula, the feedback matrix of faults requiring modification is:

\[ R_i = B_i^{-1}(A_i - A) + B_i^{-1}BR \]  \hspace{1cm} (8) 

By continuously adjusting formula (8), complete fault compensation can be realized, thus realizing fault tolerance control\(^7\). Through the above algorithm, real-time monitoring and effective extraction of rolling bearing fault features are carried out so as to optimize the fault tolerance mechanism of machine learning rolling bearings according to its calculation results.

2.2 Rolling Bearing Fault Diagnosis Platform Based on Machine Learning

Combined with the above algorithm, diagnosis and correction are carried out for known fault parameters, and the bearing fault diagnosis control circuit is optimized. The reliability of the bearing operation circuit is related to whether the whole can run normally or not, and is also an important means to improve the reliability\(^8\). Its purpose is to adjust by the controller, so that the rolling bearing fault of the traction transmission device can still maintain good performance. Since any power tube failure will cause the circuit to run out of phase, hardware redundancy is the main factor of circuit control. Driven by the control signal, it has discrete characteristics. According to the physical laws of the circuit, two conditions of controller and hardware redundancy are fully considered. Its working principle is shown in the figure.

**Fig. 2 Platform Circuit Optimization**

The DC filt capacitor is divided into two part of circuits, that capacitors are C1 and C2 respectively, the bidirectional thyristor VT1 is used for connecte the two capacitors with the center O, and VT2 is used for connecting C3 with the center O to form a circuit topology with fault tolerance capability. During normal operation, the bidirectional thyristors VT1 and VT2 are in an off state, and the circuit is an equivalent circuit\(^9\). At this time, the power tube VM1 triggers a pulse and the fault is lost. The fault tolerance function is used to turn off VM3, trigger VT2 and VT1 to remain off, and the circuit is reconstructed into a half-bridge circuit. However, when VM2 triggers a pulse and a fault is lost, the diagnostic function is used to turn VM4 off, triggering VT1 and VT2 to remain off, and the circuit is reconstructed into a half-bridge circuit\(^10\). After the circuit is reconstructed, the fault-tolerant controller should make corresponding adjustments according to the target changes to ensure that the fault-tolerant control is within a certain range. Using embedded software development platform, KeilVision4 as development tool and KeilC/C++ as compiler, fault-tolerant control technology route is
designed. Initialization is started by periodic real-time interruption. The purpose of fault diagnosis is to take corresponding diagnostic measures according to different fault characteristics, eliminate and compensate the faults, and ensure safe and reliable operation of equipment. The control process of fault diagnosis is shown in the figure.

As can be seen from the figure, the diagnosis and control process of the platform includes fault feature collection, result display, signal processing, fault detection and fault tolerance control. Fault-tolerant control is to adopt corresponding fault-tolerant control methods according to fault feature information before or after the rolling bearing of traction drive fails, so as to ensure accurate detection and fault-tolerant treatment of rolling bearing faults, and thus improve the safety of rolling bearing operation.

2.3 Realization of Intelligent Fault Diagnosis for Rolling Bearings
The automatic diagnosis program of rolling bearing fault can be designed in different levels, especially when programming PLC logic controller, the level of equipment fault should be fully considered and the logic control flow should be designed reasonably. When inputting the fault location points, the lowest fault input information should be designed into the PLC logic controller program as much as possible, as shown in the figure, so as to obtain more fault detection information and provide a basis for the rolling bearing fault automatic diagnosis system.
It can be seen from the figure that when analyzing the fault points of rolling bearings, the fault point program should be recorded and analog fault diagnosis should be carried out. In order to obtain the system fault situation, the state information feedback of all fault detection points received by PLC internal registers should be used, and the fault point program should be recorded. The A-side belt signal IR4.02 is the input joint point. When the system uses the A-side belt equipment to operate normally, the input value of the joint point becomes 1. When the system cannot operate using the A-side belt equipment, the input value of the joint point becomes, indicating that a fault has occurred. The following formula is required to record the signal jump. Let L1 and L2 be respectively the upper limit and the lower limit of signal jump at the same fault point, and their distribution sets are respectively:

\[
S = R \sum_{g_{i} \cap g_{j} = \beta} \left\{ L_{1}(g_{i})L_{2}(g_{j}) \right\}
\]

Where: \( \beta \) Under normal circumstances, the signal strength; \( S \) is \( g_{i} \) and \( g_{j} \)'s product of all credibility. From this, the function of credibility can be obtained as follows:

\[
f(g_{k}) = \sum_{g_{i} \cap g_{j} = \beta} \frac{L_{1}(g_{i})L_{2}(g_{j})}{1-S}
\]

Where: \( g_{k} \) Signal strength under abnormal conditions; when \( g_{k} = \beta \), \( f(g_{k}) = 0 \). Among them: \( i, j, k=1,2,\cdots, n \); if \( g_{i} \) and \( g_{j} \) When the same fault point does not occur at the same time, the recording signal will jump. The jump of this signal is recorded in R31.00 and is used as a memory for recording fault information. Due to the multi-bit nature of the internal memory, it is possible to record the causes of various faults at the same time. Sometimes there are more than one cause of equipment failure, and one failure point often causes simultaneous failures in multiple locations. Therefore, in the recording process, to find the first failure point, the process needs to be implemented according to PLC programming. The specific flow is shown in the following figure
As shown in the figure, the analog module in the diagnostic program needs to be used to receive the signal from the current transmitter and convert the signal into a numerical value, which is compared with the maximum value and the minimum value within the allowable range of the system. The maximum value and the minimum value are related to the parameter changes of the actual system operation. If the numerical value is within the limit value range, it means that the equipment has no fault and can operate normally. If the value is not within the limit value range, it means that the equipment has failed and cannot operate normally. Therefore, it is necessary to use serial communication to quickly read all kinds of fault information in the internal memory of PLC logic controller, and to link the upper computer with one or more PLC by using Host Link mode to realize serial communication. In the process of communication, the PLC needs to receive the command frame sent from the upper computer and respond immediately after receiving it. If there is no fault in the equipment, the PLC will automatically give feedback to the upper computer. However, the upper computer needs to know the status of the PLC by the numerical value in the storage, and can also obtain fault information by controlling the PLC by the upper computer.

3. Analysis of experimental results
In order to verify the effectiveness of the intelligent diagnosis method for rolling bearing faults based on machine learning. Taking a axle box rolling bearing as a test object, the application time domain and fault time domain characteristic parameters are extracted, four characteristic parameters such as mean square root, peak value, pulse factor and waveform factor are selected as conditional attributes, rolling bearing normal state, inner ring fault, outer ring fault and roller fault are decision attributes, these parameters are normalized, and the data processing results are shown in the table.
Table 1 Data Normalization Processing Results

| Data set | mean square Value root | Peak value | pulse Factor | Waveform Factor | output state |
|----------|------------------------|------------|--------------|----------------|--------------|
| Q1       | 0.1975                 | 0.2293     | 0.5542       | 0.0500         | Normal       |
| Q2       | 0.1208                 | 0.4280     | 0.7362       | 0.0460         | Inner ring failure |
| Q3       | 0.2002                 | 0.1239     | 0.4748       | 0.0500         | Inner ring failure |
| Q4       | 0.2082                 | 1.0002     | 0.2568       | 0.5800         | Outer ring failure |
| Q5       | 0.1786                 | 0.4771     | 0.8405       | 0.0920         | Roller failure |
| Q6       | 0.3899                 | 0.1825     | 0.5524       | 0.0443         | Normal       |

After normalization, the same models are comparable. The debugging of test equipment is shown in the following table.

Table 2 Test Equipment Commissioning

| Device name | interface testing | Independent module debugging | Comprehensive function debugging | Control rate adjustment |
|-------------|-------------------|-------------------------------|---------------------------------|-------------------------|
| Clock       | √                 |                               |                                 |                         |
| serial communication |                               |                               |                                 |                         |
| I2C communication |                               |                               |                                 |                         |
| Sensor      | √                 |                               |                                 |                         |
| actuator    | √                 |                               |                                 |                         |
| Navigation  | √                 |                               |                                 |                         |

After all the testing equipment has been debugged, the test analysis will begin. After the preparation for the above test, the fault-tolerant control based on time series analysis is compared with the fault-tolerant control based on fault compensation. The inner ring, outer ring and roller have faults, and the actual and estimated results of fault parameter diagnosis are shown in fig. 6.
Fig. 6 shows the actual and estimated results of fault parameters, wherein the actual value of the inner ring fault parameter is in a straight line form, and the fault parameter is 1.01 when the time is 0-2 seconds. For 2-14 seconds, the fault parameter is 0.71. The estimated value is in the form of positive curve fluctuation. When the time is 0-2 seconds, the fault parameter is 1.01; In 2-5 seconds, the fault parameter decreases from 1.01 to 0.89; In 5-14 seconds, the fault parameter decreases from 0.89 to 0.69.

The actual value of the outer ring fault parameter is also in a linear form, and when the time is 0-2 seconds, the fault parameter is 1.01; For 2-14 seconds, the fault parameter is 0.85. The estimated value is in the form of reverse curve fluctuation. When the time is 0-2 seconds, the fault parameter is 1.01; For 2-6 seconds, the fault parameter decreases from 1.01 to 0.67; At 6-14 seconds, the fault parameter rises from 0.67 to 0.88.

The actual and estimated values of roller fault parameters are both in the form of linear-curve fluctuation, which is basically consistent. When the time is 0-2 seconds, the fault parameter is 1.43; In 2-14 seconds, the fault parameter decreases from 1.4 to 0.6. According to the above results, the initial state of comparative analysis is $x(k) = [2 \quad 4]^T$ Time zero input response curve, as shown in figure 7.

Fig. 7 zero failure parameter input response curve

In the figure, 1, 2 and 3 respectively represent the response curve when the inner ring fails, the response curve when the outer ring fails, and the response curve when the roller fails. According to the zero-input response curves under the three fault forms, the accuracy of fault-tolerant control based on time series analysis and fault-tolerant control based on fault compensation are compared and analyzed, and the results are shown in the following table.
Table 3 Comparative Analysis of Precision of Two Controls

| time/s | Based on time series analysis | Diagnostic Control Based on Fault Compensation |
|--------|------------------------------|-----------------------------------------------|
|        | Inner ring | outer ring | roller | Inner ring | outer ring | roller |
| 2      | 0.52       | 0.62       | 0.31   | 0.95       | 0.94       | 0.97   |
| 4      | 0.51       | 0.65       | 0.46   | 0.94       | 0.92       | 0.96   |
| 6      | 0.42       | 0.64       | 0.38   | 0.92       | 0.98       | 0.96   |
| 8      | 0.41       | 0.58       | 0.42   | 0.98       | 0.96       | 0.95   |
| 10     | 0.38       | 0.54       | 0.38   | 0.98       | 0.98       | 0.95   |
| 12     | 0.32       | 0.52       | 0.37   | 0.95       | 0.96       | 0.94   |
| 14     | 0.31       | 0.49       | 0.21   | 0.95       | 0.93       | 0.93   |

Inner loop: based on time series analysis, the control accuracy reaches the highest 52% when the time is 2s and the lowest 31% when the time is 14s. Fault-tolerant control based on fault compensation achieves the highest control accuracy of 98% when the time is 8 and 10 seconds, and the lowest control accuracy of 92% when the time is 6 seconds.

Outer loop: based on time series analysis, the control accuracy reaches the highest 65% at 4s and the lowest 49% at 14 s.: Fault-tolerant control based on fault compensation achieves the highest control accuracy of 98% when the time is 6 and 10 seconds, and the lowest control accuracy of 92% when the time is 4 seconds.

Roller: Based on time series analysis, the control accuracy reaches the highest 46% at 4s and the lowest 21% at 14s; Fault-tolerant control based on fault compensation achieves the highest control accuracy of 97% when the time is 2s and the lowest control accuracy of 93% when the time is 14s.

The analysis results show that the control accuracy of fault-tolerant control based on fault compensation is higher no matter which kind of fault occurs, thus confirming the rationality of the fault diagnosis method of rolling bearing based on fault compensation.

4 Concluding remarks
Based on the vibration signals of rolling bearings, a fault diagnosis control method is designed, which can be widely applied to the fault diagnosis and fault tolerance control of rolling bearings, and the fault tolerance control based on time series analysis is taken as the control group for experimental analysis. The experimental results show that this design has higher diagnosis and control efficiency, effectively improves the operation efficiency of traction drive, and also proves the feasibility of this design scheme. Based on this, it is further extended to the problem of robust fault-tolerant control with uncertain parameters in the case of bearing failure.

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