Research on Error Monitoring Model of CNC Machine Tool Based on Artificial Intelligence

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Abstract. In recent years, according to the rapid development and increasing application of artificial intelligence technology, the mechanical structure of modern CNC machine tools is becoming more and more complicated, and the automation level of CNC machine tools is constantly increasing. Research on a set of artificial intelligence-based CNC machine tool error monitoring model is of great significance to China's industrial development. This article is a more in-depth and systematic study of the health monitoring system of CNC machine tools, especially high-end (such as five-axis linkage) CNC machine tools, multi-source fusion technology that supports high-reliability maintenance decisions, and key components of CNC machine tools based on artificial intelligence Fault monitoring and early warning. Based on the artificial intelligence SOM neural network learning algorithm, this paper designs a rolling bearing fault monitoring and early warning model architecture, studies the multi-source data fusion method based on DS evidence theory, and proposes and implements a self-organizing feature mapping network fault monitoring algorithm and adaptive ARMA The fault early warning algorithm improves the calculation efficiency of the rolling bearing monitoring diagnosis and early warning under the premise of ensuring accuracy. The experimental results show that when the sampling value is greater than 980 groups, the degradation value increases more until the bearing is in a failure state.

Keywords: Artificial Intelligence Neural Algorithm, CNC Machine Tool Error, Condition Monitoring, Error Recognition

1. Introduction

With the rapid development of artificial intelligence technology in China, it is more and more widely used in CNC machine tools. How to improve the reliability of CNC machine tools is crucial. It is necessary to use CNC machine tool fault monitoring and early warning technology to detect the trend
of machine tool degradation in time. And the necessary maintenance measures are applied. In addition, in order to meet the processing needs of high-speed, high-precision, composite processing, etc., the mechanical structure of modern CNC machine tools is becoming more and more complicated, and the automation level of CNC machine tools is constantly increasing \cite{1-2}. Relying only on the existing maintenance methods of the enterprise, its capability is far from enough. Therefore, it is of great practical significance to realize the fault monitoring and early warning technology of CNC machine tools \cite{3-4}.

The monitoring and evaluation of the health status of CNC machine tools is used to evaluate whether the CNC machine tools meet the relevant accuracy index requirements \cite{5-6}. At the same time, the error data of the machine tool can be obtained through the monitoring of the health status of the CNC machine tool, which provides a basis for achieving the high-precision manufacturing and processing performance of the data machine tool \cite{7-8}. The health of equipment, such as the health of CNC machine tools, refers to the normal body, normal operation, normal production products, normal production efficiency, normal life, etc. In normal and production and processing, the error is low, there are no unqualified products, and the equipment is not faulty. No damage, no low efficiency, no aging phenomenon \cite{9-10}.

In this paper, the artificial intelligence SOM neural algorithm is used to carry out research on the monitoring diagnosis and early warning of rolling bearings of CNC machine tools. The model structure of rolling bearing monitoring diagnosis and early warning is studied; the scheme of rolling bearing fault monitoring and early warning is designed; combining the characteristics of rolling bearing fault monitoring and early warning, this paper proposes A self-organizing feature map network fault monitoring algorithm and an adaptive ARMA fault early warning algorithm are implemented. Under the premise of ensuring accuracy, the calculation efficiency of rolling bearing monitoring diagnosis and early warning is improved. Experimental results show that the proposed method has a good application effect in the artificial intelligence environment.

2. Proposed Method

2.1. Artificial Neural Network Model of CNC Machine Tool Error Monitoring Neural Network

(1) SOM neural network structure

The network is a teacherless, self-organizing, self-learning network. The proposed network structure is to divide the network into different spatial regions, and each region has different response characteristics to external input information. The SOM network model consists of the following 4 parts.

1) An array composed of processing units. The array generates the "discrimination function" of the corresponding network model based on external event inputs.

2) Automatic comparison and selection mechanism. By calculating the above "discrimination function" of the network model of each processing unit, the output result is obtained, and by comparing the output results, the processing unit with the largest output value is selected.

3) With local interconnection effect. The interconnection between various processing units on this
network realizes the basis of network self-learning. Due to the interconnectivity of the various processing units on the network, each processing unit is not independently selected.

4) With adaptive process. Through repeated learning, the output value of the discriminant function is maximized.

(2) SOM neural network learning algorithm

The SOM network can automatically recognize the similarity between the input data, and use the "proximity principle" to configure the approximate input on the network unit.

1) Initialization of SOM network

The initial value of the weight between the input level and the mapping layer is a random number. The connection weight between the input neuron and the output neuron is adjusted to a lower weight. The outgoing neuron next to the neuron link is selected to form the set \( S_j \); where \( S_j(0) \) represents the set of adjacent neurons of neuron \( j \) at time \( i = 0 \), and \( S_j(t) \) represents the set of adjacent neurons of neuron \( j \) at time \( t \). The area \( S_j(t) \) continues to shrink as time \( t \) increases.

2) Input of input vector

Assign the input vector \( X = (x_1, x_2, x_3, \ldots, x_m)^T \) to each neuron in the input layer.

2.2. Design of Fault Monitoring and Early Warning Algorithm Based on Adaptive ARMA

The ARMA model is also called a linear regression prediction model, which is a combination of a self-existing model and a moving average. For a constant random normal signal with a mean value of zero, it is represented by a time series as \( \{X_t\} \). If the sequence has a linear relationship with its historical information, it is called the \( n \)th series of automatic acceleration models and is declared as AR (\( n \)) model.

If the time series saves the noise signal added to the system at each recording time, it is called the \( m \)-th moving average model, which is denoted as the MA (\( m \)) model:

\[
x_t = a_t - \theta_2 a_{t-2} - \ldots - \theta_m a_{t-m}
\]  

(1)

If \( \{X_t\} \) is not only affected by the \( \{X_{t-1}\}, \{X_{t-2}\}, \ldots, \{X_{t-n}\} \) values of the previous \( n \) steps, but also related to the interference \( \{a_{t-1}\}, \{a_{t-2}\}, \ldots, \{a_{t-n}\} \) of the previous \( m \) steps, using multiple linear regression and time series self-processing, a general ARMA model can be obtained:

\[
x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_n x_{t-n} - \phi_1 x_{t-1} - \phi_2 x_{t-2} - \ldots - \phi_n x_{t-m} + a_t
\]  

(2)

According to the characteristics of the ARMA model, the input and output information of the system must be a constant random sequence. In practical applications, most random sequences are non-static random sequences. The changes must be analyzed first, and then adjustments must be made using the time series method to meet the prediction function of the method.
The usual fitting method is to obtain the sequence difference or the sequence after multiple differences according to the \( y_i = x_i - x_{i-1} \) difference, and finally obtain the fixed sequence. The processing method satisfying the exponential distribution, cosine distribution, etc. is the same as the above method.

### 2.3. Comprehensive Geometric Error Modeling of CNC Machine Tools Based on Multi-body Theory

The total error of the relative position of the tool and the workpiece in the machine tool coordinate system determines the machining accuracy of the workpiece. The above errors are obtained by synthesizing the errors of each component of the machine tool. The comprehensive geometric error model of CNC machine tool is to determine the relationship between the two, which is also the theoretical basis for error compensation. Whether the model is accurate directly determines the final effect of error compensation. The determination of the error model depends on different error measurement methods. It is necessary to directly measure the error vector of each point in the working space of the CNC machine tool. Under the existing measurement conditions, not only the measurement efficiency is low, but also has no practical significance. In order to improve the measurement efficiency, it is necessary to establish an error model, and indirectly obtain the error value of each point in the machine tool motion space through the model solution.

(1) Comprehensive geometric error modeling of CNC machine tools with arbitrary structure

Due to the influence of the machine tool during the machining process or the accuracy of the machine tool itself, various errors inevitably exist, such as thermal deformation, wear, and force deformation. But no matter what kind of error, the final position is reflected in the mutual position error between the workpiece and the tool. To compensate for the above error, you need to correct the corresponding transformation matrix.

(2) Geometric error modeling of the five-axis CNC machine tool with double turntable

The comprehensive error model of the five-axis machine tool represents the amount of error caused by the relative position between the tool and the workpiece in the machine motion space. In order to improve the machining accuracy of the machine tool, the error value needs to be fed back to the control system, and participate in the error compensation calculation in the control system to improve the accuracy performance of the machine tool, so the accuracy of the integrated error model reflects the accuracy of the feedback amount, which in turn affects the final positioning accuracy of each axis.

This article takes the double turntable numerical control machine tool as the research object, carries on the kinematics solution. The kinematic structure of the machine tool includes: three linear axes marked as X, Y, and Z axes; two rotary axes, respectively marked as C 'and B'. The kinematic chain description form is drawn according to the machine tool structure. The steps are:

1) Establish the coordinate system and necessary reference coordinate system connected with each kinematic pair, and determine the conversion matrix between the connected coordinate systems, so as to realize the description of the kinematics of each kinematic pair.

2) Determine the transformation matrix of coordinate tool system and reference coordinate system chain, workpiece coordinate system and reference coordinate system coordinate system.
3) Establish the geometric relationship between the tool coordinate system and the workpiece coordinate system. According to the relative geometric relationship between the tool and the workpiece, combined with the two coordinate conversion relations, the position description of the tool in the workpiece coordinate system is finally determined.

Since the comprehensive error model of the five-axis machine tool is based on the kinematics model of the five-axis machine tool, the kinematic model of the machine tool is first established below.

(3) Rolling bearing fault monitoring and early warning program for state maintenance

Bearing error monitoring and maintenance methods include condition monitoring, error monitoring, and early warning and decision-making maintenance, which is also the main content of health prediction and management. By acquiring the signal of the working status of the rolling bearing, preprocessing and outputting the signal characteristics, combined with the big data analysis, the position of the rolling bearing can be monitored in real time to determine the fault characteristics of the rolling bearing. Based on the identified fault characteristics, the final recognition of the failure mode and prediction of the rolling bearing voltage, including monitoring the deterioration of the rolling bearing state and diagnosis of the failure mode. Combined with the subsequent decision-making technology, closed-loop feedback monitoring and adjustment are applied to the test.

3. Experiments

3.1. Experimental Test

In order to verify the effectiveness of the neural algorithm in this article, this article chose the Center for Intelligent Maintenance Systems (IMS), NASA Bearing Data Set provided by the University of Cincinnati. The data contains three different data sets. The data was collected from the NI DAQ 6062E card. The data set represents three test processes. From the beginning of the test to the failure of the bearing, each experiment collected the entire process of disassembling different bearings. Each record of each set of data is a vibration signal lasting 1 second, the corresponding frequency of each record is 20 kHz, and the number of samples contained in each sample space is 20480. Try to record every 10 minutes.

3.2. Experimental Collection

In Test 1 #, select 2200 samples, and in Test 2 #, select 1000 samples. For ease of control, the above sample data is marked as a state, which divides the state into a degenerate state and a stable state. In this experiment, it is known that the test bearing test ends with a fault condition. In this document, a 10% limit is set to distinguish between two status classes.

4. Discussion

4.1. Analysis of Fault Monitoring Algorithm of ARMA Adapter

Use the fault monitoring algorithm based on the ARMA adapter to determine the distance and distance deviation between each sample state and the normal state, and determine the degradation value of the
bearing under consideration by this value. The results of the decomposition test are shown in Table 1 below.

**Table 1. Analysis of bearing degradation values**

| Number of sample groups | 0      | 200    | 400    | 600    | 800    |
|-------------------------|--------|--------|--------|--------|--------|
| Degradation value(Test one) | 0.754  | 0.245  | 0.219  | 0.376  | 0.947  |
| Degradation value(Test two) | 0.715  | 0.271  | 0.207  | 0.427  | 0.875  |

As can be seen from Table 1 above, the result of the decomposition trend of Test 2 # Bearing 1 is that when the sample value is in the top 500 groups, the decomposition value of the bearing is less than 0.1 and there is no significant change. The extreme point is approaching. When it is greater than 730 groups, the demotion value will first decrease slightly and then increase rapidly. When there are more than 980 teams, the degradation will increase further until the bearing is in failure mode.

4.2. Artificial Intelligence Fault Monitoring SOM Neural Network Algorithm Analysis

In order to verify the rationality of the test results, Bearing1 and Bearing4 are in the same working position, and the two decomposition curves are similar. Bearing4's failure time is delayed, the failure point time is after 984 points. In addition, Bearing2 and Bearing3 are also in the same operating position, and you can see the similarities between Bearing2 and Bearing3. They have also undergone sharp changes in the downgrade of about 150 groups. The experimental results are shown in Figure 1 below.

**Figure 1. Early warning curve of bearing fault detection**
Figure 1 shows the evaluation of the decomposition values in Bearing2-4 using sensors in different directions. The results show that the decomposition curves of the two are similar. Based on the above analysis, the test results verify that the destructuring evaluation results obtained from the customized ARMA error warning algorithm are consistent with the actual bearing degradation process.

5. Conclusion

The diagnosis results based on the artificial intelligence network algorithm SOM can distinguish different types of damage through the dark blue area. According to the actual test results, during the 1 # test, the failure modes of Bearing3 and Bearing4 are inner ring failure and ball wear, respectively. In Test 2 #, the Bearing1 fault function is an outer ring fault. This result is consistent with the diagnosis result of the SOM neural network algorithm, indicating that the location and warning diagnosis algorithm is effective in this paper. The application research of CNC machine tool fault monitoring and early warning based on artificial intelligence technology needs further research. At present, research in this area is still in its infancy. Artificial intelligence provides technical advantages for achieving reliable equipment failure and early warning, but it also faces great challenges.

References

[1] Xiaopeng Y, Guofu Y, Guangming L I. Positioning Error of Feed Axis Decouple-separating Modeling and Compensating Research for CNC Machine Tools[J]. Journal of mechanical engineering, 2016, 52(1):184.

[2] He Z Y, Fu J Z, Xu Y T. New method to measure angular position errors of rotational axis of CNC machine tool[J]. Zhejiang Daxue Xuebao (Gongxue Ban)/Journal of Zhejiang University (Engineering Science Edition, 2015, 49(5):835-840.

[3] F. Li, H. Wang, T. Li. Research on Thermal Error Modeling and Prediction of Heavy CNC Machine Tools[J]. Journal of Mechanical Engineering, 2016, 52(11):154-160.

[4] WANG Wei, TAO Wenjian. Research on Characteristic of Test Specimen for Five-axis CNC Machine Tools[J]. Journal of mechanical engineering, 2017, 53(1):101.

[5] Zhiming Feng. Compensation for CNC Machine Tools Comprehensive Error Based on Interpolation Algorithm[J]. Journal of Information & Computational Science, 2015, 12(4):1599-1605.

[6] He Z Y, Fu J Z, Chen Z C. Thermal error measurement of spindle for 5-axis CNC machine tool based on ball bar[J]. Guangxue Jingmi Gongcheng/Optics and Precision Engineering, 2015, 23(5):1401-1408.

[7] Ma Y, Wang H F, Sun W, et al. Multivariate Correlative and Combined Thermal Error Model for the CNC Machine Tool with Experimental Validation[J]. Dongbei Daxue Xuebao/journal of Northeastern University, 2017, 38(5):700-705.

[8] Joanna MICHALOWSKA, Jerzy JÓZWIK. Prediction of the parameters of magnetic field of CNC machine tools[J]. Przeglad Elektrotechniczny, 2019, 1(1):136-138.
[9] Li X, Yang Q, Qiu H, et al. Small-sample MTBF estimation for a CNC machine tool[J]. Revista de la Facultad de Ingenieria, 2016, 31(7):131-143.

[10] Sheng Z, Lu F, Wu L. Domain mapping of product service system oriented on CNC machine tools[J]. Control Engineering & Applied Informatics, 2015, 17(4):59-70.