Research Early Mechanical Failure of CNC Motorized Spindle Prediction Method Base on D-S Evidence Theory Information Fusion

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Abstract. Early mechanical failure of CNC milling motorized spindle having a hidden and complexity is difficult to quickly and accurately identify early machines failure of CNC milling. In this paper, early latent subtle abnormal vibration signals of motorized spindle is detected by PeakVue. Fuzzy neural network diagnosis for each partial signal, and then the sub-diagnosis as evidence, the use of D-S evidence theory to the global final diagnosis, and further improve the early fault recognition rate. Using method of rough set theory data mining obtain processing parts of the surface roughness characteristics of data, which have established the surface roughness of the spectral characteristics of the database. Subsystems, we use FNN fault diagnosis, then the sub-diagnosis as evidence, we use the D-S evidence theory to the global final diagnosis, and further improve the early fault recognition rate. The results show that: This early fault diagnosis model fuzzy neural network and data fusion technology, which is the electrical mechanical failure early prediction accuracy spindle higher generalization ability.

Introduction

CNC milling machine spindle is the main part of the production process, it was found CNC milling spindle has a mechanical problem misdiagnosed, long maintenance cycle and other issues in production. To be able to find fault in advance to avoid large spindle failure, the paper motorized spindle CNC milling machine for the study of milling vibration, noise, temperature, etc. were detected by detecting various signals and trends to predict, can grasp the operational status of equipment and we found that the variation, predict the likelihood of early failure of the spindle to prevent timely detection of abnormal operation signal, so that timely adjustments [1, 2].

Method of Signal Acquisition

Micro Vibration Signal Acquisition. When CNC milling spindle because early mechanical failure, various signals relatively weak, which gives the signal acquisition and processing has brought a lot of difficulties. PeakVue is a new diagnostic technique for rolling bearings and gear fault diagnosis developed vibration signal analysis method for capturing a given time interval in the time-domain waveform peak. Applications PeakVue of technology can find abnormal mechanical vibration signal, especially in the early potential and subtle abnormal signal. When the metal-to-metal collision occurs, it will produce stress waves. Early spalling fatigue, gear and bearing defects, friction and wear and shock wave will cause stress. PeakVue that is through the collection and monitoring of these transient stress waves, and get a peak period occurs and convert the spectral analysis [3, 4].

Surface Roughness Information Collection. Rough set theory is an effective treatment is inconsistent, incomplete data mining information, has the advantage of handling massive data reduction aspects. In addition, the rough set model using only the information provided by the data itself, without modeling to design the model structure and set the model parameters, it has been used to predict the number of complex, large-scale uncertain systems [5, 6].

Electric Spindle Early Fault Diagnosis Model D -S Evidence Theory Fusion

Structure of FNN. FNN is a fuzzy theory and neural networks combine the two products. Nature, people are accustomed to using fuzzy information in logical thinking, judgment and reasoning. Fuzzy theory is on this basis, through the membership function with serial and parallel rules for fuzzy information processing. It has been proved theoretically: fuzzy logic system is able to arbitrary precision approximation of a nonlinear function; and the neural network with nonlinear mapping ability, has a close link between the two. Structure Fuzzy Neural Network consists of three functional modules, one fuzzy module, the input signal is fuzzy processing, introducing membership functions that enable more accurate training sample failure; the second is the ANN learning inference module, which uses artificial neural network with a certain algorithm for CNC machine tool spindle servo system fault diagnosis; the third is clear module, which ultimately determine the cause of the failure based on membership artificial neural network output vector to complete the neural network output mode to the diagnostic results clear process, fuzzy neural network structure shown in Fig. 1[5,6].

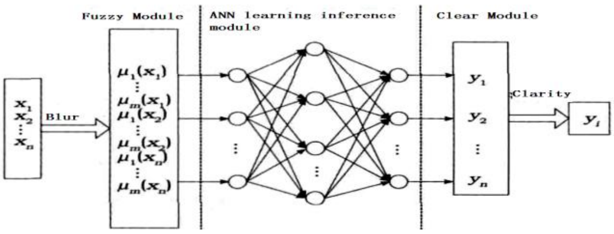

Figure 1. Structure of FNN

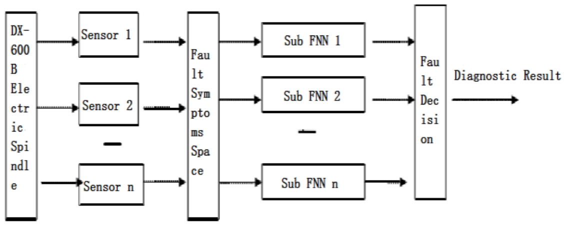

Figure 2. FNN Fault Diagnosis Based on Information Fusion Framework

Model of Fault Diagnosis. In this paper, based on the decision-making level information DS evidence theory fusion diagnosis model includes data processing, feature local diagnosis and decision-level fusion of three modules, the structure shown in Fig. 2[6].

D-S Evidence Theory The basic strategy is to evidence collection is divided into several parts that are irrelevant, and were using them to identify the framework for independent judgment, and then use a combination of rules to combine them. Dualistic situation as an example, assume that Bel_1 Bel_2 and confidence are two functions on the same frame of discernment Θ, where Θ is the sample space, that is the power set of the set of propositions made a statement incompatible set 2^{Θ} configuration. m_1 and m_2 corresponding basic probability assignment function, m1 and m2 are the focal elements A_1, A_2, ..., A_n and B_1, B_2, ..., B_n, and assumptions[8,9]:

$$K = \sum_{A_i \cap B_j} \mathrm{m}_1(A_1)\ \mathrm{m}_2(B_2) < 1 \tag{1}$$

Where: K represents the degree of conflict between the two pieces of evidence. When K = 1 when, for the whole conflict, this time D - S combination rule cannot be used; when K <1, completely non-conflict, this time, D - S can be used in combination rule. The probability assignment function m: $2^{\Theta} \rightarrow [0,1]$ for basic probabilities for all basic probability assignment of non-empty set A proposition A has the distribution function (trust in Proposition A's):

$$m(A) = \frac{\sum_{A_i \cap B_j} \mathrm{m}_1(A_1)\ \mathrm{m}_2(B_2) < 1}{1-K} \tag{2}$$

The promotion of the above twenty-two fusion rules to more evidence combination, the combined effects of a plurality of functions corresponding to the confidence level of the results can also function with a plurality of straight-confidence and said:

$$m(A)=\frac{\sum_{A_i\cap B_j=A}\mathrm{m}_1(A_i)\ldots\mathrm{m}_n(A_j)}{1-\sum_{A_i\cap B_j=A}\mathrm{m}_1(A_i)\ldots\mathrm{m}_n(A_j)} \tag{3}$$

D-S Evidence Theory in the key is how to construct the basic probability of each focal element, the output of the neural network and fuzzy comprehensive evaluation as D-S evidence theory combination of evidence credibility. Network error between the actual output and the desired output of the fuzzy neural network is:

$$E_n=\frac{1}{2}\sum_j(t_{nj}-y_{nj})^2 \tag{4}$$

Where: E_n is the n-th characterization network error vector; t_{nj} for the n-th vector characterizing the j-th output neuron expectations; y_{nj} is n-j output neuron actual value of the n characterizing vector [10]. Basic probability values of fuzzy neural network diagnosis will normalize after the results are substituted into the formula (5), to give each sample i-th failure mode m (A_i), the network error same treatment as D-S Evidence Theory the degree of uncertainty m (Θ), construction of D-S evidence theoretical probability distribution value:

$$\begin{cases} m(A_i)=y(A_i)/S \\ \sum_{i=1} y(A_i)+E \end{cases} \tag{5}$$

Where: A_i represents failure mode; i = 1, 2, ..., n; y (Ai) fuzzy neural network diagnostic results. By D-S Evidence Theory method multiple fuzzy neural network diagnostic results in the decision-making level fusion, thereby obtaining fully reflect the equipment running diagnostic results.

Simulation and Analysis

In this paper, CNC milling machine (DX-600B) mechanical failure data as an example, in this way only the vibration signal and the accuracy of two road surface judgment result information fusion. Select E1 spindle fever, intermittent pauses when E2 spindle heavy cutting; E3 spindle work faint noise, E4 machining accuracy drops (surface morphology of a certain law), E5 machining accuracy drops (surface morphology no significant law) as the fault characteristic semaphores, forming a sample by normalization process after analysis, detection database. Because each input networks often have a different meaning and a different physical dimension, we need to enter sample normalized, normalized formula is as follows:

$$T = X - X_{\min}/X_{\max} - X_{\min} \tag{6}$$

Where: X is the original data; X_{max} and X_{min} to the maximum and minimum values of the original data; T is the transformed data, ie, the target data; article 100 select group of samples from the instance data, the sample group of 10 after normalization which data shown in table 1.The main fault is defined 5 types: A_1 spindle bearing preload is too large, A_2 spindle bearing damage, A_3 spindle motor spindle connected with the too loose, A_4 spindle assembly balancing bad, A_5 spindle drive gear wear. Establish sample database. The vibration sensor data, the accuracy of detecting surface data into the fuzzy neural network is trained, expected output and simulation results are shown in Table 2 and Table 3, using the formula (1) method provides the basic structure of the probability of each fault in Table 4.

Similarly, the surface accuracy of the test data into the fuzzy neural network training simulation, and the results are shown in Table 5, and then construct the basic probability assignment (2).The results are shown in Table 6. Finally, more than two sub-diagnosis decision level fusion, coming in Tables 4 and 6 are fused to form a fusion diagnostic model based on Decision Level D-S evidence theory fusion results shown in Table 7, Table 4, Table 6 and Table 7 comparison, can be found after the fusion substantially improved diagnostic confidence in decision-making.

Table 1 One of a sample treated normalized

No.	E_1	E_2	E_3	E_4	E_5	Fault type
1	0.923	0.125	0.453	0.101	0.012	A_1
2	0.754	0.012	0.723	0.231	0.841	A_2
3	0.120	0.964	0.012	0.023	0.120	A_3
4	0.623	0.121	0.823	0.786	0.453	A_4
5	0.726	0.102	0.789	0.862	0.354	A_5

Table 2 The desired output of the detection data

Number of Groups	F_1	F_2	F_3	F_4	F_5
Group 1	1	0	0	0	0
Group 2	0	1	0	0	0
Group 3	0	0	1	0	0
Group 4	0	0	0	1	0
Group 5	0	0	0	0	1

Table 3 Vibration signal subsystem failure diagnosis model simulation results

Number of Groups	A_1	A_2	A_3	A_4	A_5
Group 1	0.901	0.245	0.365	0.256	0.284
Group 2	0.324	0.832	0.246	0.612	0.714
Group 3	0.123	0.264	0.812	0.142	0.231
Group 4	0.146	0.679	0.303	0.836	0.641
Group 5	0.234	0.756	0.230	0.664	0.862

Table 4 Vibration signal output subsystem basic probability distribution obtained

Number of Groups	$m(A_1)$	$m(A_2)$	$m(A_3)$	$m(A_4)$	$m(A_5)$	$m(\Theta)$
Group 1	0.902	0.244	0.366	0.255	0.282	0.012
Group 2	0.323	0.833	0.247	0.613	0.713	0.122
Group 3	0.124	0.265	0.813	0.143	0.232	0.031
Group 4	0.145	0.678	0.304	0.835	0.640	0.021
Group 5	0.236	0.757	0.231	0.665	0.863	0.012

Table 5 Surface accuracy subsystem failure diagnosis

Number of Groups	A_1	A_2	A_3	A_4	A_5
Group 1	0.900	0.255	0.375	0.276	0.294
Group 2	0.324	0.822	0.256	0.622	0.724
Group 3	0.133	0.274	0.812	0.162	0.241
Group 4	0.146	0.679	0.303	0.836	0.651
Group 5	0.239	0.757	0.255	0.674	0.852

Table 6 Surface accuracy probability distribution function subsystem configuration

Number of Groups	$m(A_1)$	$m(A_2)$	$m(A_3)$	$m(A_4)$	$m(A_5)$	$m(\Theta)$
Group 1	0.902	0.256	0.373	0.279	0.295	0.010
Group 2	0.321	0.823	0.255	0.623	0.723	0.112
Group 3	0.132	0.273	0.813	0.163	0.243	0.041
Group 4	0.143	0.678	0.302	0.835	0.652	0.022
Group 5	0.238	0.756	0.256	0.672	0.853	0.014

Table 7 Level fusion results of D-S evidence theory decision

Number of Groups	m(A_1)	m(A_2)	m(A_3)	m(A_4)	m(A_5)	m(Θ)
Group 1	0.982	0.056	0.073	0.079	0.129	0.001
Group 2	0.121	0.923	0.155	0.123	0.123	0.012
Group 3	0.132	0.073	0.933	0.163	0.043	0.012
Group 4	0.143	0.178	0.012	0.955	0.152	0.002
Group 5	0.038	0.156	0.056	0.172	0.953	0.004

Conclusion

For high-speed milling machine (DX-600B) Early diagnosis of mechanical failure, for D - S Evidence Theory in the application of basic probability assignment is difficult to determine the problem, using a plurality of fuzzy neural network output subsystem constructed D-S Evidence Theory basic probability assignment. Simulation results show that: The diagnostic system can effectively solve the motorized spindle mechanical failure uncertainty and increased electrical spindle early mechanical failure diagnosis accuracy, the results more reliable.

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