

Research on Fault Diagnosis Technology of CNC Machine Tool Based on Machining Surface Roughness

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Abstract. This paper studied the relationship between the spindle fault and the roughness characteristics, by surface roughness of machining. Spindle common fault is divided into the spindle system is not balanced, the spindle system is not right, the spindle system has a transverse crack and the spindle system rolling bearing failure. The characteristic amount of the machining surface is extracted by CCD laser speckle surface roughness measurement technique. Machine fault information and rough surface relationship were established through the adaptive network-based fuzzy inference system (ANFIS), to achieve the machine tool spindle fault diagnosis. The results indicate that the roughness characteristic can accurately diagnose the machine tool spindle fault and can be an effective method to study the spindle fault of the machine tool.

Introduction

Spindle as a key power components, widely used in various types of high-speed CNC machine tools, machinery manufacturing plays an extremely important role in the field. With the spindle speed is getting higher and higher, the performance and status of the detection and control has become increasingly important. If the occurrence of degradation, often produce the wrong measurement signal, resulting in improper operation and other serious consequences, and thus CNC machine tool spindle fault diagnosis method has become a more important issue[1].

Research Status of Fault Diagnosis Technology

Domestic and foreign fault diagnosis technology research shows that the use of fault diagnosis technology, the accident rate and equipment maintenance costs are greatly reduced and improve the productivity. The research results of modern fault diagnosis methods have made great progress in this field. The research results mainly focus on lifting wavelet transform, holographic theory, main fold learning and commonly used diagnostic techniques.

The use of lifting wavelet is very wide, mainly used in signal noise reduction and fault feature extraction. Ana M. Gavrovska and so on for different test signals to select different thresholds, for a purpose of noise reduction and feature extraction, each wavelet filter can be decomposed into the lifting format. ZHANG Yong-xue focuses on the improvement of real signal noise reduction by lifting wavelet transform. Song Guoming uses the lifting wavelet transform to optimize the fault feature, accurately reflect the fault signal characteristic information, and obtain the better fault feature vector through the classification function. Duan Chendong et al. Extract the transient shock fault feature by adding the sliding window based on the lifting wavelet transform. JIANG Quan-sheng et al. Proposed a fault pattern recognition method, using LE algorithm to extract the inherent low-dimensional manifold of the original fault signal, improve fault classification and recognition ability[2,3].

At the same time, other theories are also applied to fault diagnosis, and achieved fruitful research results. Such as particle swarm optimization algorithm, genetic algorithm, support vector machine (empirical mode decomposition, neural network, etc.) have also been very good development and

achieved some success, but the application of the machining rough shape to predict the CNC machine tool spindle The fault information is also no one to study.

Measurement of Surface Roughness of Parts

Surface roughness is closely related to the performance of the part. Although the theoretical formula can be obtained through the theoretical formula, but in the actual process, due to cooling and lubrication, tool status, chip and other uncertainties, the theoretical roughness value and the actual value will be different, The consistency of the entire surface of the machined part or all parts roughness. At present, domestic and foreign scholars extensively use a variety of sensors to collect the cutting force, vibration, displacement and current and other signal data during processing, through the establishment of process signal characteristics and surface quality of the approximate relationship model to achieve the measurement of roughness[4].

Principle of Three - Dimensional Roughness Measuring Instrument. The digital image processing based on the speckle image is based on the hardware speckle acquisition system. As shown in Fig. 1, the system is a block diagram of the CCD speckle acquisition system. The system is composed of a laser, a CCD camera, a computer and a lens. The computer built-in camera Of the image transmission acquisition card. The laser system is simple, the laser is irradiated to the surface of the standard flat grinding specimen at a fixed angle. The CCD camera collects the speckle image of the standard sample surface in the corresponding fixed position, the computer saves the image transmitted by the camera through the image acquisition card, Spot image for digital image processing.[5]

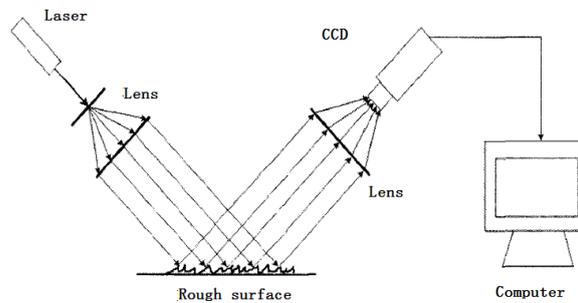


Figure 1. Finite 3D roughness meter acquisition system block diagram

Establishment of 3D Roughness Base Plane. The basic principle of three-dimensional evaluation of surface topography is to use a polynomial function to represent the surface to be measured. The function is established on the basis of the least squares principle, and the polynomial function is derived from the derivative, and then the polynomial function is obtained. Coefficient to establish the least squares mid-plane of the contour surface.

The evaluation of the three-dimensional surface roughness parameter is based on the least squares midpoint of the contour, which refers to the surface in which the sum of the squares of the contours of the sampling points in the contour surface is the minimum.

For example, the given surface $z(x, y) = f(x, y)$ can be expressed as polynomial (1):

$$\varepsilon = \sum_{i=1}^m \sum_{j=1}^n (z(x_i, y_j) - f(x_i, y_j))^2 \quad (1)$$

(m * n is the number of measuring points, $i = 0, 1, \dots, m; j = 0, 1, \dots, n$). Let $\varepsilon^2 = \min$, obtain the value of the parameter in the equation, this method of determining the coefficient is called the least squares method. The principle of equivalence is expressed as follows: the most reliable value of the

measurement is the square of the variance (the square of the standard deviation), or the square of the uncertainty, or the sum of the squares of the residuals is the minimum. This is a mathematical optimization technique that uses the square of the minimized error to find the best function of a series of data matches.

Roughness Feature Extraction. For the same material, the same processing method to generate the surface, the fault information is mainly reflected in the micro-surface texture of the parts and convex and concave, so the accuracy of the parts of the roughness measurement requirements are relatively high, you can extract the surface texture direction S_{td} , The maximum depth of the contour, and the maximum peak height, S_p , for fault assessment. At the same time, the surface root mean square deviation S_q , the surface ten point height S_z , the bottom depth S_v in the parameter selection also need to be considered. The parameters are calculated as follows:

1) the root mean square deviation of the surface S_q : S_q is a frequently used parameter, which indicates the standard deviation of the sample in the statistical field. However, S_q cannot be reflected by the interval distribution and the frequency of the micro-surface deep valleys and the peak The

2) surface ten point height S_z in a sampling area, the surface ten point height represents the depth of the five deepest pits and the arithmetic mean of the height of the five highest vertices. For the three-dimensional evaluation, the definition of different vertices has a great influence on the S_z measurements, but a large number of experiments show that the vertices defined in the relevant region have relatively stable results. However, different sampling area size and location and sampling accuracy of the S_z has a very significant impact, so use it to characterize the stability and effectiveness cannot be effectively guaranteed.

3) Maximum peak height of the contour S_p : In the evaluation area D , the maximum value of the z -coordinate on the roughness surface, that is, the maximum height of the contour surface relative to the reference plane. It is also an important parameter that reflects the characteristics of surface roughness.

4) the texture of the surface direction S_{td} in the conventional processing technology processing surface, will produce a certain processing texture, the parameters that the surface texture direction, the metric is relative to the y axis (set the x -axis for the measurement direction) The texture direction of the surface is determined by the surface spectral moment and the cross autocorrelation function. S_{td} is only suitable for the main texture of the surface. In general, the surface of the general accuracy level, there are more obvious texture direction, while the ultra-precision surface, there is no obvious texture direction.

5) Contour maximum peak height S_p : In the evaluation area D , the maximum value of the z -coordinate on the roughness surface, that is, the maximum height of the contour surface relative to the reference plane. It is also an important parameter that reflects the characteristics of surface roughness.

6) the maximum depth of the outline of the depth of S_m in the assessment area D , rough surface z coordinate minimum value, take the absolute value of the contour after the maximum valley depth, that is, to measure the contour surface below the reference surface of the maximum distance. It is another important parameter for the roughness surface feature evaluation, which is echoed with the maximum peak, and has the same important significance[6].

ANFIS Model.

1)ANFIS structure

For ease of illustration, it is assumed that the ANFIS system with Takagi - Sugeno fuzzy rules has two inputs x and y , one output z , and contains the following two rules.

$$\text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = a_1x + b_1y + c_1 \quad (2)$$

$$\text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = a_2x + b_2y + c_2 \quad (3)$$

The corresponding ANFIS structure is shown in Fig. 2The connection between nodes only indicates the flow of the signal, and there is no weight associated with it. The square node represents

the node with adjustable parameters, and the round node indicates that there is no tunable node. Among them, only the first layer and the fourth layer has adjustable parameters[7].

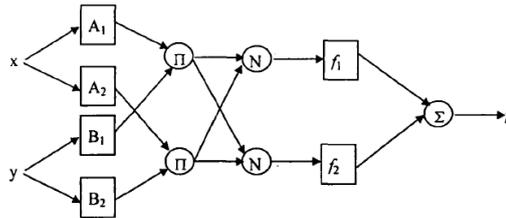


Figure 2. Finite ANFIS structure diagram

The function of each layer follows the first 1-5 layers[4]:

Tier 1 fuzzy input variables, x and y determine the membership of fuzzy sets and the output is

$$o_i^1 = \mu_{A_i}(x) \tag{4}$$

According to the chosen form of membership function, you can get the appropriate set of parameters, called the antecedent parameters. All $\{\sigma_i, d_i\}$ parameter set consisting of the front piece, the learning process in the sample, e.g. the value, select a common Gaussian membership function, the formula (4) can be adaptively adjusted in ANFIS each parameter.

$$\mu_{A_i}(x) = \exp\left[-\frac{\|x - d_i\|^2}{\sigma_i^2}\right] \tag{5}$$

Tier 2 output is the product of the input signal, and its meaning is a sample of the rules activation intensity.

$$o_i^2 = \varpi_i = \mu_{A_i}(x)\mu_{B_i}(y) \tag{6}$$

The fourth layer, go fuzzy computing nodes, each node to calculate the output of the corresponding rules.

$$o_i^3 = \varpi_i = \frac{\omega_i}{\omega_1 + \omega_2} \tag{7}$$

Layer 4 to blur compute nodes, each node to calculate the corresponding.

$$o_i^4 = \varpi_i f_i = \varpi_i(a_i x + b_i y + c_i) \tag{8}$$

Output rules Layer 5 to calculate the output of all the rules and.

$$o_i^5 = f = \frac{\sum_i \varpi_i f_i}{\sum_i \varpi_i} \tag{9}$$

Structure visible from the ANFIS, ANFIS and fuzzy inference system equivalent. Using a neural network, fuzzy reasoning has the ability to self-learning.

Establishment and Experiment of Fault Diagnosis Model for CNC Milling Machine

Spindle System Common Faults. 1)the spindle system is not balanced. Due to the design, manufacture, installation, processing, spindle long-term operation, electromagnetic interference and

other reasons will cause the spindle system quality eccentricity, when the spindle system is running, this eccentricity will cause the spindle system vibration, the spindle system is not balanced. The vibration frequency and the slew frequency are the same. The curve in the time domain is similar to that of the sine wave. The axis of the axis is represented by a circle or an ellipse. If it is a spindle caused by a coupling, the vibration frequency and the rotation frequency are the same. The roughness of the surface can be extracted. The surface texture direction Std has the characteristics of circle or ellipse, the maximum depth of the contour and the maximum peak height Sp of the contour is more than 5% of the standard value.

2)the spindle system is not correct. Spindle system misalignment may be due to manufacturing, installation, support deformation and other reasons, the main form of performance for the coupling is not correct. Couplings are not divided into parallel, angle and both misaligned. The main features are: parallel to the situation will often appear radial vibration, vibration frequency of the frequency of the second frequency of the frequency, but also the existence of multi-frequency vibration; maximum vibration mainly in the coupling on both sides of the bearing, vibration The value increases with the increase of the load; the spectrum shows the radial double frequency and quadruple frequency vibration is obvious. The roughness characteristic can extract the surface texture direction Std radial direction, the surface ten point height Sz is greater than the standard value of 10% or more.

3)the spindle system transverse crack. When the spindle is defective, the lateral crack will be generated on the spindle. When the spindle system is running, the operating state of the spindle system is often affected by the lateral crack. The influence of the opening and closing of the crack on the performance of the spindle system is very serious. When the crack is closed, the vibration characteristic of the main shaft is the same as that of the axis, and the roughness characteristic can extract the surface. When the crack is closed, the vibration characteristic of the spindle is the same as that of the axis. Texture direction Std radial, surface ten point height Sz greater than the standard value of more than 5%.

4)rolling bearing failure. Rolling bearings are generally composed of four basic elements: the rolling body itself (the ball or roller, inner ring, outer ring and cage. When the bearing rotates, these elements interact mechanically; their inherent defects cause the bearing force and The rotation of the rotation axis causes the spindle error to move, and each bearing part has its own shape error, and such shape error will produce the error movement in the spindle. Compared with the basic frequency is the diameter ratio of the bearing element and the rotating element The roughness characteristic can be extracted from the surface texture direction Std is uncertain, the surface ten point height Sz is greater than the standard value of 2-5%. Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads- the template will do that for you[8-9].

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

Fault Mode and Fault Analysis. The fault features $E = \{E1, E2, E3, E4\}$ are: E1 surface texture direction Std has a circle or ellipse characteristics, the maximum contour depth Sm and contour maximum peak height Sp is greater than the standard value of more than 5%. E2 surface texture direction Std radial, surface ten point height Sz greater than the standard value of 10% or more. E3 surface texture direction Std radial, surface ten point height Sz greater than the standard value of more than 5%. E4 surface texture direction Std is uncertain, the surface ten point height Sz is greater than the standard value of 2-5%. The main reason for these failures $F = \{F1, F2, F3, F4\}$ are: F1 spindle system is not balanced, F2 spindle system is not right, F3 spindle has cracks, F4 rolling bearing failure. Moreover, the relationship between these phenomena and causes is complex, with obvious nonlinearity and coupling.

Fuzzification of Fault and Acquisition of Training Samples. ANFIS is used to diagnose the NC machine tool. First, the fuzzy rules are determined and the data is fuzzified according to the importance of fault features and cause appearance. The fault feature $F1 \rightarrow F4$ is described by two fuzzy sets of "normal" and "high". The feature $F4$ is represented by two sets of "low" and "normal" modules. According to the expert experience, the trigonometric function is used as the membership of the input variable. The function of the membership function of each input variable is shown in Fig.3

Combined with the experience accumulated in the maintenance of the machine tool and the experience of the relevant experts, the fuzzy description of the degree of failure (Table 1) is obtained, and the fuzzy regularization library corresponding to the fault feature and reason is obtained. In order to get a more robust diagnostic model, the fuzzy rules should be as comprehensive as possible.

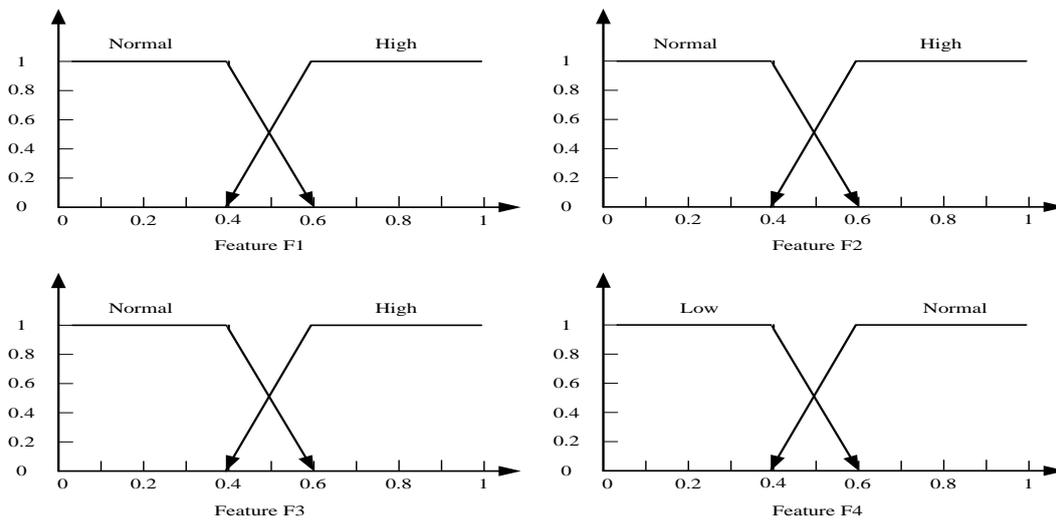


Figure 3. Finite Membership function distribution

Table 1 Fuzzy Description

The Degree of Presence Cause	Members hip
Must	0.8~1
Possible	0.6~0.8
Unclear	0.4~0.6
Not too possible	0.2~0.4
NO	0~0.2

Table 2 Symptom Fuzzy Relationship With The Corresponding

Fault No.	E1	E2	E3	E4	F1	F2	F3	F4
1	0	0	0	0	0	0	0	0
2	0.8	0	0	0	1	0	0	0
3	0	0.8	0	0	0	1	0	0
...
29	0	0	0.8	0.8	0	0	0	1
30	0	0.8	0	0.8	0	0	1	1

Model Training and Comparison of Results. In the training model, 20 of the 30 groups of samples in Table 2 were randomly selected as training samples and 10 groups as test samples. ANFIS learning was reduced to the adjustment of the front parameter (nonlinear parameter) and the latter parameter (linear parameter). For the front parameter of equation (5) and the posterior parameters of equation (8), the BP algorithm (back propagation algorithm) and the least squares estimation algorithm are used to adjust the parameters, called the mixing algorithm, according to the relationship between input and output. One of the iterations of the hybrid learning algorithm consists of two steps: Step 1: The parameters of the front part are fixed and the input signal is passed forward along the network until the fourth layer. The least squares estimation algorithm is used to adjust the parameters of the latter[10]. After that, the signal continues along the network Forward to the output layer (ie, layer 5); Step 2, the error signal will be transmitted back along the network, and use the BP algorithm to adjust the front parameters[11]. By using the hybrid learning algorithm, we can get the global optimal point of the posterior parameter for a given preamble parameter, which can not only reduce the dimension of the search space in the gradient descent method, but also can greatly improve the convergence rate of the parameter. It can be seen that the test output only number 5, a group of fault categories cannot be accurately obtained, the remaining five groups of faults can be accurately identified.

Table 3 Diagnostic Model Test Output And Expected Output

Fault No.	Test Output				Expected Output				Fault Feature
	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>F4</i>	
1	0.90	0.10	0.21	0.28	1	0	0	0	E1
2	0.57	0.88	0.16	0.33	0	1	0	0	E1,E2
3	0.22	0.49	0.92	0.16	0	0	1	0	E2,E3
4	0.23	0.29	0.32	0.96	0	0	0	1	E4
5	0.13	0.23	0.85	0.86	0	0	0	1	E3,E4
6	0.37	0.62	0.32	0.86	0	1	0	1	E2,E4

Conclusion

The fault data of the machine tool spindle are characterized by the extraction of the parameters of the surface roughness. The experimental data prove the effectiveness, but the fault diagnosis accuracy is not accurate enough, and the fault diagnosis model still needs to be further improved.

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References

- [1] Zhang Jian, based on the image of the workpiece surface roughness detection system research [D], Nanjing University of Aeronautics and Astronautics, 2011.
- [2] Xu Xiao Mei, Hu Hong. Development of non-contact surface roughness measurement in last decades [J]. ICMTMA 2009, 1:210-213.

- [3] MAO Chun-yu, ZHOU Guang-WEN, XU Yu-kun, Research of Rre-Rotating Machinery Fault Diagnosis Based on Fuzzy Neural Network And Information Fusion, International Symposium on Computer, Consumer and Control, Taiwan, 2014.06.10-12.
- [4] Wang Jiahai, Huang Jiangtao, Shen Bin, and so on. Research Status and Prospect of CNC machine tools Intelligent Fault Diagnosis [J]. Machinery manufacturing, 2014 (5): 30 – 32.
- [5] FERREIRO S, SIERRA B, IRIGOIEN I, et al. A bayesiannetwork for burr detection in the drilling process [J]. Journal of Intelligent Manufacturing, 2012, 23 (5): 1463-1475.
- [6] JOS ÉVICENTE ABELLÁN NEBOT, FERNANDO ROMEROSUBIRON. A review of machining monitoring systems based on artificial intelligence process models [J]. International Journal of Advanced Manufacturing Technology, 2010, 47 (1/2/3/4): 237-258.
- [7] Wang Jianguo, WU Qing, Qin Bo, and so on. Prediction with oxygen [J] PSO support vector machine BOF. Foundry Technology, 2014 (8): 1806-1809.
- [8] Wang Jiahai, Huang Jiangtao, Shen Bin, and so on. Research Status and Prospect of CNC machine tools Intelligent Fault Diagnosis [J]. Machinery manufacturing, 2014 (5): 30 – 32.
- [9] SUN Yan-jie, AI Chang-sheng. Study on tool wear state monitoring based on fusion of cutting and cutting force parameters [J]. Combined Machine Tool and Automation Processing Technology, 2011 (05).
- [10] XIAO Hong-jun. Fuzzy Control and Experiment of Inverted Pendulum Based on Sugeno Model [J]. Journal of Xi'an Engineering University, 2011 (05).
- [11] MAO Chun-yu, ZHOU Guang- Wen, TIAN Mei, Research Early Mechanical Failure of CNC Motorized Spindle Prediction Method Base on D-S Evidence Theory Information Fusion, IMEICI 2016, Shengyang, china, 2016.09.24-26.