International Journal of Hybrid Information Technology
Vol. 9, No.8 (2016), pp. 367-376
http://dx.doi.org/10.14257/ijhit.2016.9.8.32

Fault Diagnosis Model Based on Multi-level Information Fusion for CNC Machine Tools

Wen Yan, Tan Ji-wen, Zhan Hong and Sun Xian-bin

Department of Mechanical Engineering, Qingdao Technological University, Qingdao 266052, China
wy2001qd@126.com

Abstract

The difficulty of CNC machine tools fault diagnosis is bigger than other general equipments because of the complex structure and the coupling among subsystems. The fault diagnosis model based on multi-level information fusion and hybrid intelligence is studied to improve reliability of fault diagnosis. Information from built-in sensors is used to monitor the status of CNC machine tools. The diagnosis principles of internal parameters-motor current, torque, temperature and following error are analyzed. Internal information and external sensors are two main sources which provide data to diagnosis. In order to detect effective fault signal, features of time domain, frequency domain and time-frequency domain are extracted. All these features constitute the feature set. The features are selected by the method of Kernel Principal Component Analysis (KCPA). Then the sensitive feature set is obtained. The method of multiple classifier fusion based on fuzzy comprehensive evaluation is researched. The determination method of weight based on information entropy is proposed. This diagnosis model has been tested feed system mechanical fault diagnosis of CNC machine tools and the results show which is effective and versatile.

Keywords: *information fusion, CNC machine tools, fault diagnosis, fuzzy comprehensive evaluation*

1. Introduction

CNC machine tools are automated machine tools which are equipped with numerical control system. They can change tools automatically and achieve complex curve or surface machining with high precision, stable machining quality, which have become the foundation of equipment manufacturing industry. Because working in the state of high-speed, variable load, frequent reversing, vibration, friction, *etc.*, the performance of CNC machine tools typical parts are easy to failure. Faults, especially failures in mechanical part will take a long period maintenance time and cause a huge economic loss [1]. But most self-diagnosis system of CNC machine tools don't have the ability to diagnose mechanical faults [2-3]. Therefore research on condition monitoring and fault diagnosis method for numerical control devices mechanical fault is very crucial.

2. Diagnosis Model Based on Information Fusion and Hybrid Intelligence

In order to improve accuracy and reliability of diagnosis, the hybrid intelligence diagnosis model based on information fusion is proposed, as shown in Figure 1. Multi-level fusion and various intelligent technologies are combined together in this fault diagnosis model and many measurements are taken to reduce the uncertainty in diagnosis process. CNC machine tools internal information source and external sensors source provide comprehensive and complete information to diagnosis. The energy features are

ISSN: 1738-9968 IJHIT

extracted of signals after EMD decomposition, with the features extracted of time domain, frequency domain form the feature set reflecting fault information from various aspects. To simplify the classification structure and improve diagnosis accuracy, the features are selected by the method of Kernel Principal Component Analysis (KCPA). Then the sensitive feature set is obtained. These sensitive features are input into different classifiers and the primary diagnosis results are accessed. All the primary results of classifiers' are fused by the method of fuzzy comprehensive evaluation to gain the final diagnosis result.

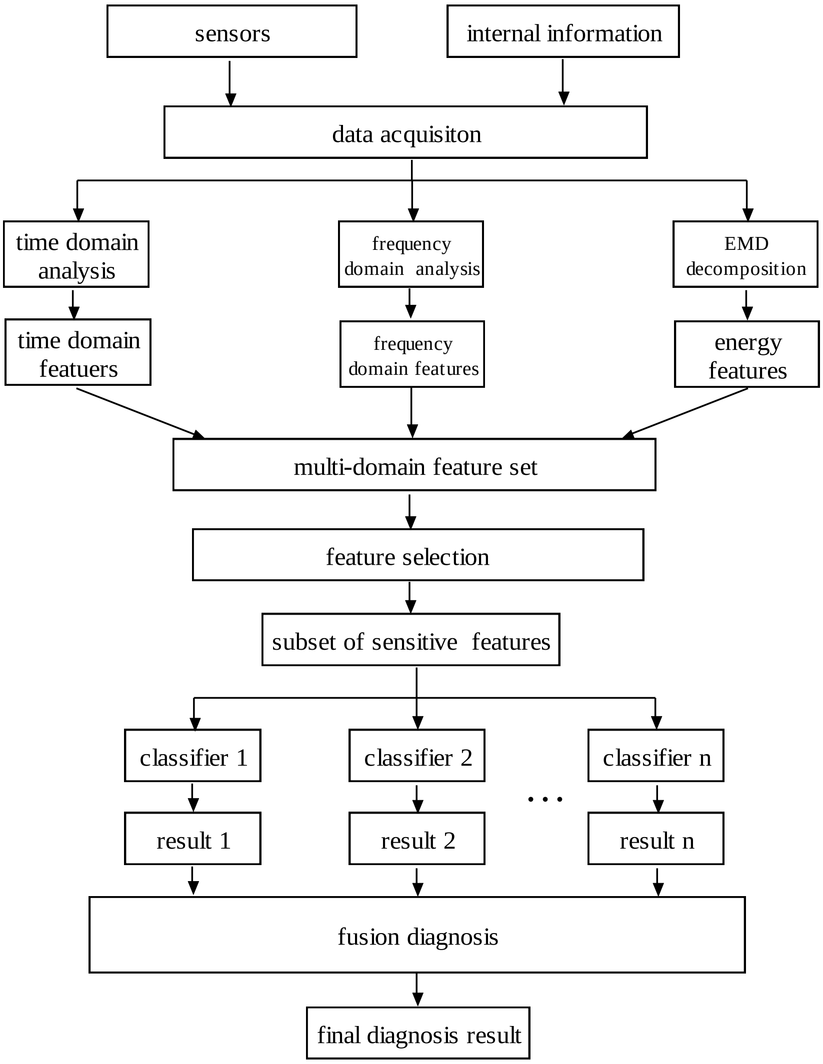


Figure 1. Fault Diagnosis Model Based on Information Fusion and Hybrid Intelligence

3. Condition Monitoring System Based on Multi-Dimension Information

Plenty of status information is a prerequisite to fault diagnosis. If there is no sufficient information reflecting machine running status, it would increase the uncertainty in the diagnosis process and even leads to misdiagnosis or missed diagnosis.

Many various kinds of sensors such as vibration, noise and temperature *etc*. [4]are mounted at different locations to monitor status information of machine. But any sensor is an additional structure against CNC machine tools. Installation of so many sensors becomes very inconvenient due to the limitation of machine tool structure or size. If changing the sensors mount position, signals would like to become weak because of the increase of propagation path length.

Grating, rotary encoder, current sensor, temperature sensor are equipped with CNC machine tools. The operation status of the CNC machine tools is gained in real time by itself. The built-in sensors' signals of open CNC machine tools can be achieved directly under online state [5]. The kind of internal information with high reliability is a new and reliable information source to monitor CNC machine tools status.

4. Diagnosis Principles of Internal Parameters

4.1. Motor Torque

In feed system of CNC machine tool, the torque of motor can be calculated by Eq. (1)[6].

$$T_m - T_l = J\frac{d\omega}{dt} \tag{1}$$

Where J is moment of inertia constant feed system, ω is instantaneous angular velocity of motor, T_l is load torque which includes two parts,

$$T_l = T_c + T_f \tag{2}$$

Where T_f is torque caused by friction, T_c is cutting torque.

So

$$T_m = J\frac{d\omega}{dt} + T_c + T_f \tag{3}$$

If feed system is moving at constant speed in no-load status, so $J\frac{d\omega}{dt} = 0$, $T_c = 0$, then

$$T_m = T_f \tag{4}$$

If wear failures occur in mechanical parts of transmission system, friction must increase which causes friction torque increasing inevitably to overcome friction. So the value of motor torque’s change is impacted by fault that is an important parameter to monitor.

4.2. Temperature of Motor

The power density of motor S is closely related to the volume and its power. And high power density means high loss density and high temperature.

$$S = \frac{P_{out}}{V_M} \tag{5}$$

Where P_{out} is the output power of motor, V_M is the characteristics volume.

According to the equation

$$P = T \cdot \omega \tag{6}$$

The output power of motor can be defined as Eq.(7).

$$P_{out} = T_m \cdot \omega = J\frac{d\omega}{dt}\omega + T_f\omega + T_c\omega \tag{7}$$

When faults occur, the output power of motor P_{out} will increase. So the power density of motor S increases which lead to the raise of temperature. So the temperature of motor is an important monitoring parameter for CNC machine tools diagnosis system.

4.3. Following Error of Shaft

Following error is the deviation of the calculated value and the actual location value that reflects dynamically the performance of the machine tool's shaft and the static positioning accuracy.

Mechanical failure is one of the main reasons to lead to the stable value of follow error being too large. For example, failures occur in motor, mechanical connection part such as bearing, guide rail and ball screw may lead to a large follow error value. Then the follow error is one of the important parameters needed special attention in the fault diagnosis and maintenance.

5. Multi-Domain Mixing Features

In order to obtain more information reflecting the operating status of the machine comprehensively and accurately, 14 parameters of time domain and 3 parameters of frequency domain are extracted and the formulas of these parameters are shown in Table1.

Table 1. Features of Time Domain and Frequency Domain

No.	Formula	No.	Formula
1	$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$	10	$\alpha = \frac{1}{N}\sum_{i=1}^{N} x_i^3$
2	$x^{'} = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$	11	$\beta = \frac{1}{N}\sum_{i=1}^{N} x_i^4$
3	$x_{\max} = \max(x_i(t))$	12	$S = \frac{x_{rms}}{x^{'}}$
4	$x_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2}$	13	$C == \frac{x_{\max}}{x_{rms}}$
5	$x_t = (\frac{1}{N}\sum_{i=1}^{N} \sqrt{\lvert x_i \rvert})^2$	14	$C_q = \frac{\beta}{{x_{rms}}^4}$
6	$I = \frac{x_{\max}}{x^{'}}$	15	$X_{fc} = \frac{\sum_{i=1}^{n} f_i F(f_i)}{\sum_{i=1}^{n} F(f_i)}$
7	$C_e = \frac{x_{rms}}{\bar{x}}$	16	$X_{msf} = \frac{\sum_{i=1}^{n} {f_i}^2 F(f_i)}{\sum_{i=1}^{n} F(f_i)}$

8	$\sigma_x{}^2 = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2$	17	$X_{vf} = \frac{\sum_{i=1}^{n}(f_i - X_{fc})^2 F(f_i)}{\sum_{i=1}^{n}F(f_i)}$
9	$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}$		

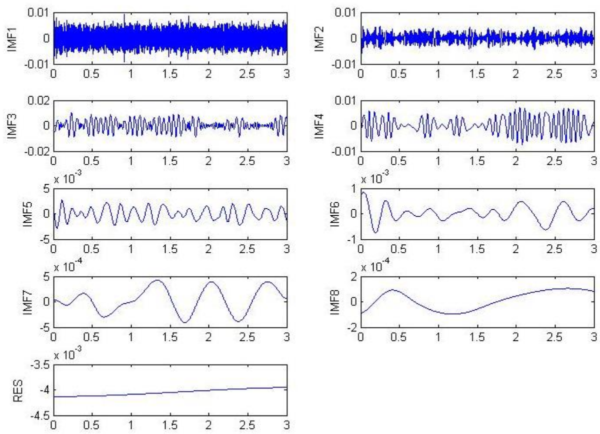
Empirical Mode Decomposition which can describe the relationship between signal frequency changes over time is suitable for analyzing non-stationary fault signal [7]. The signal is decomposed into the sum of several multi-scale signals, called the Intrinsic Mode Function (IMF)[8]. The signals of different fault types would be automatically decomposed into some frequency bands. So the signal energy distribution of various fault type is different, as shown in Figure 2.

The energy of IMF is

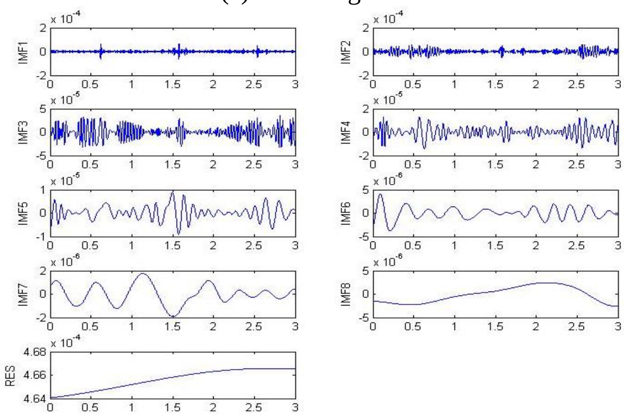
$$E_i = \int |c_i(t)|^2 dt \tag{8}$$

Where $c_i(t)$ is signal of ith IMF.

So energy features of each IMF, the feature parameters of time domain and frequency domain form the multi-domain mixing feature set to reflect failure information.



(a) inner ring fault



(b) outer ring fault

Figure 2. EMD Results of Different Faults Signals

6. Feature Selection Based on Kernel Principal Component Analysis

After feature extraction, the feature set includes a large number of features. On one hand, excessive features must increase the number of classifier input which leads to the complexity of classifier structure and increases the difficulty of classification. On the other hand, some researches indicate that too many inputs cannot get a better result because high degree of correlation between the features which must be eliminated [9].

On the basis of principal component analysis (PCA), the original data are converted into linearly separable characteristic data by non-linear mapping in method of Kernel Principal Component Analysis (KPCA). The original high-dimension features can be expressed by low-dimension principal component data. So KCPA is one of the feature dimension reduction methods commonly using in fault diagnosis field. The main steps of feature selection based on KPCA are shown in Figure 3.

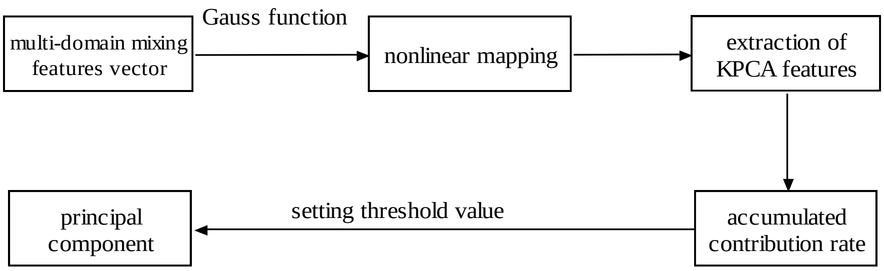


Figure 3. Feature Selection Based on KPCA

7. Multiple Classifiers Fusion Based on Fuzzy Comprehensive Evaluation

Because the classification principles and algorithm is different, so that even for the same sample, different classifiers have different diagnosis results. Any kind of classifier is not perfect which can not apply in all conditions because any classifier has its own limitations. The results of different classifiers can form the complementary relation. This is the foundation of multiple classifiers fusion.

The output of a classifier is $y_j = (y_j^1, y_j^2, \cdots, y_j^m)$ (m is the number of fault type), the classifier's output entropy is

$$H_{y_j} = \begin{cases} -K\sum_{i=1}^{m} y_j^i \ln y_j^i, \textit{the result is correct} \\ 1, \quad \textit{the result is not correct} \end{cases} \tag{9}$$

Where K is a constant which is related to the number of fault types, take $K = 1/\ln m$.

All classifiers are tested by the same samples. The entropy values of all the outputs of classifiers are calculated according to the Eq. (9). If the number of test samples is x, the average entropy of each classifier $\overline{H}_{y_j}$ is

$$\overline{H}_{y_j} = \frac{H_{y_j}}{x} \tag{10}$$

The degree of deviation

$$d_{y_j} = 1 - \overline{H}_{y_j} \tag{11}$$

Each classifier weight is

$$\omega_{y_j} = \frac{d_{y_j}}{\sum_{j=1}^{J} d_{y_j}} \tag{12}$$

The weight vector is $A = (\omega_1, \omega_2, \omega_3, \ldots\ldots, \omega_J)$. The evaluation matrix is R. Then

$$B = A \circ R \tag{13}$$

Where B is the fusion output result, '$\circ$' is fuzzy operator [10].

B is a vector which gives the possibility of various fault type. According to the principle of maximum membership, the fault type is determined.

8. Experiment

In order to demonstrate the effectiveness of the model proposed in this paper, experiments are carried out on CNC machine tools feed system. Bearing fault, ball screw fault, couplings fault, composite fault which occurs in bearing and ball screw simultaneously and normal status (seen as a particular fault type) are studied. Three measuring points are set in this experiment. At measuring point 1 and 2, three vibration acceleration sensors and a noise sensor are mounted. At measuring point 3, a vibration acceleration sensor is mounted. Measuring point distribution and sensor installation position are shown in Figure 4.

Seven international parameters including motor temperature, current, torque, actual speed, following error, control deviation and contour error are utilized [11] in this experiment.

After feature extraction, there are total 400 features. The accumulation contribution rate is set at '90%' in KPCA, the number of features is reduced to 42. The top 50 main composition accumulation contribution rate is shown in Figure 5.

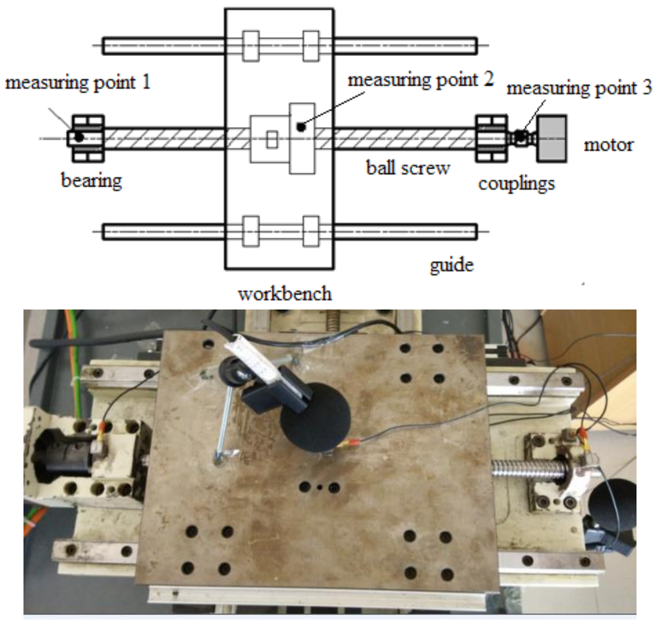


Figure 4. Measuring Points Distribution and Sensors Installation Position

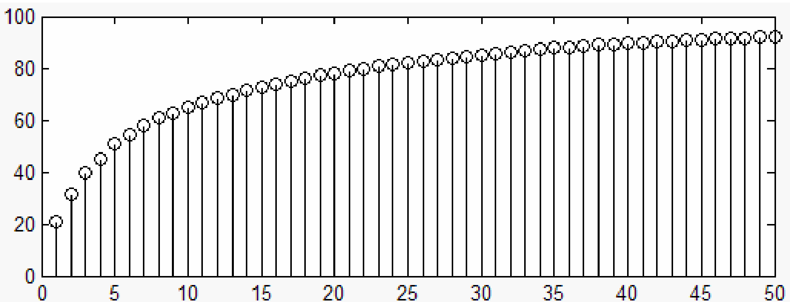


Figure 5. Accumulated Contribution Rate

Firstly three diagnosis models based on BP neural network, RBF network and SVM are set up and trained respectively. Then three kinds of models are tested using the same sample data.

According to the method described in part of 7, so A={0.45,0.10,0.45}.

In order to validate the proposed method, some samples fusion results are shown in Table 2.

Table 2. Fusion Results

No.	Fault type		Outputs of classifiers	Outputs by fusion
1	F1	BP	0.2220 0.0000 0.7726 0.0054 0.0000	0.2500 0.0145 **0.6787** 0.0410 0.0158
		RBF	0.6272 0.1357 0.0965 0.0000 0.1406	
		SVM	0.1941 0.0020 0.7142 0.0858 0.0039	
2	F1	BP	0.1071 0.0000 0.8927 0.0002 0.0000	0.3100 0.0093 **0.6707** 0.0037 0.0063
		RBF	0.8555 0.0838 0.0000 0.0134 0.0473	
		SVM	0.3917 0.0021 0.5978 0.0051 0.0034	
3	F1	BP	0.0636 0.0000 0.0099 0.9265 0.0000	**0.4847** 0.0210 0.0089 0.4539 0.1704
		RBF	0.4657 0.1620 0.0000 0.2118 0.1605	
		SVM	0.9100 0.0107 0.0099 0.0351 0.3430	
4	F1	BP	0.2563 0.0000 0.0905 0.6527 0.0004	**0.6117** 0.0119 0.0702 0.3009 0.0052
		RBF	0.7963 0.1055 0.0702 0.0000 0.0281	
		SVM	0.9261 0.0031 0.0498 0.0160 0.0050	
5	F1	BP	0.0207 0.0000 0.3929 0.5798 0.0066	0.1423 0.0130 **0.5606** 0.2675 0.0165
		RBF	0.6256 0.1222 0.1522 0.0000 0.1000	
		SVM	0.1566 0.0017 0.8191 0.0146 0.0079	
6	F1	BP	0.0000 0.0000 1.0000 0.0000 0.0000	0.0414 0.0473 **0.5812** 0.0767 0.2535

		RBF	0.2794 0.3858 0.0767 0.0000 0.2580	
		SVM	0.0300 0.0194 0.2744 0.1704 0.5059	
		BP	0.0000 1.0000 0.0000 0.0000 0.0000	
7	F2	RBF	0.1272 0.2664 0.0000 0.2011 0.4052	0.0186 **0.8657** 0.0181 0.0336 0.0639
		SVM	0.0131 0.8646 0.0403 0.0300 0.0520	
		BP	0.0096 0.9904 0.0000 0.0000 0.0000	
8	F2	RBF	0.0000 0.2937 0.1322 0.2728 0.3013	0.0089 **0.8782** 0.0284 0.0365 0.0480
		SVM	0.0101 0.8960 0.0337 0.0206 0.0396	

There are 55 samples diagnosis results of three kinds of classifiers existing confliction among 279 test samples. 41 samples can be diagnosed the fault type correctly though fusion diagnosis. So the accuracy of diagnosis is nearly 95% after classifier fusion. The experiment result proves the effectiveness of the proposed diagnosis model.

9. Conclusions

(1) Built-in sensor information of CNC machine tools is used in this model, with the traditional external sensor information sources, to monitor the running status of machine tools. The two types of information sources form the complementation relation effectively, so as to reduce or eliminate the uncertainty in diagnosis process caused by incomplete data.

(2) Due to the structure complexity of CNC machine tools, the failure characteristics are not obvious. So signal processing methods of time domain, frequency domain and time-frequency domain are used to find more effective features.

(3) In the diagnosis model different artificial intelligence techniques such as artificial neural networks and fuzzy comprehensive evaluation are used and the combination of these techniques makes any of them work effectively.

(4) Information fusion can be divided into data layer fusion, feature layer fusion and decision fusion. In multi-level fusion process new information and new knowledge is discovered. The diagnosis accuracy is improved by multi-information fusion.

Acknowledgements

This study is supported by the National Natural Science Foundation of China (No. 51075220), the Research Fund for the Doctoral Program of Higher Education (No. 20123721110001) , Basic Research Projects of QingDao City Science and Technology Plan (No. 12-1-4-4-(3)-JCH) and Project of Shandong Province Higher Educational Science and Technology Program (No. J13LB11).

References

[1] L. Guo, J. Chen and G.-W. Wang, "Modeling of equipment performance degradation assessment system based on multi-Agent system", Computer Integrated Manufacturing Systems, no.3,**(2008)**, pp.494-498.
[2] A. J. Álvares, J. C. Espíndola Ferreira, "Teleoperation of a CNC turning center through the Internet", Journal of Materials Processing Technology, vol. 179, no.1, **(2006)**, pp.251-259.
[3] M.-L. Qi, "Application Research of Integrated Technology of Intelligent Fault Diagnosis to NC Machine Tool Fault Diagnosis", **(2010)**.
[4] S.Y. Liang, R. L. Hecker and R. G. Landers, "Machining Process Monitoring and Control: The State-of-the-art. Journal of Manufacturing Science and Engineering", no.12, **(2004)**, pp.297-310.
[5] P. Volker, "MANFRED Weck. Sensorless Machine Tool Condition Monitoring Based on Open NCs, IEEE Power Engineering Society", International Conference on Robotics and Automation, **(2001)**, pp. 3104-3108.
[6] H. Yang, "Study on NC machine servo system detection based on built-in sensors", Manufacturing Technology & Machine Tool, no.6, **(2012)**, pp.153-158.
[7] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis", Proceedings of the Royal Society of London, **(1998)**, pp.903-991.
[8] W.-H. Dong, X.-E. Li, X.-Guo, Z.-L. Lin and Li, "A Bidimensional Empirical Mode Decomposition Method for Fusion of Multispectral and Panchromatic Remote Sensing Images", Remote sensing, no.9, **(2014)**, pp. 8446-8448.
[9] J.-S. Yuan, H.-K. Shang, Y. Wang and S. Jin, "Pattern recognition for partial discharge based on correlation coefficient matrix and probabilistic neural networks", Power System Protection and Control, no.13, **(2013)**, pp.110-115.
[10] L.-B. Yang and Y.-Y Gao , "Principium of fuzzy mathematics and its application (5th Edition)", South China University of Technology Press, Guangzhou, **(2011)**, pp.100-104.
[11] L.-Y. Wu, "The Ball Screw Fault Diagnosis of CNC Machine Tools Based on Rough Set Neural Networks", **(2012)**.

Authors

Wen Yan, She received her M.S. degree from Qingdao Technological University in the year of 2005. Now she is a lecturer in Department of Mechanical Engineering, Qingdao Technological University. Her research interest is mechanical system dynamic monitoring and fault diagnosis.