Research and Development on Intelligent Cutting Tools with Capability of On-line Monitoring and Prediction

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Abstract. Cutting-tool wear would affect machining accuracy, machining efficiency and machining cost. The on-line monitoring for cutting-tool wear would help monitor running state of cutting-tool in real time, handle accidents in time, reduce scrap occurrence during machining and cut down the cost caused by cutting-tool breakage. By the way of experimental research, wavelet analysis, neural network and grey theory, this article established a prediction model based on grey theory and wavelet neural network, developed an intelligent cutting-tool system with on-line monitoring and prediction, and which realize the real-time monitoring of the cutting-tool wear state and could help predict the abnormal condition of the cutting-tool in time. This system has some certain promotion significance.

1. Introduction
With the continuous development of automobile, aerospace, energy, medicine, new materials and new technology, Cutting-tool is developing towards the trend of compounding, specialization, high speed and high precision. In addition to the improvement of cutting-tool technology and material technology, it would be significant to realize on-line monitoring and prediction for cutting-tool to improve the forming quality of workpiece and the working condition of cutting-tool. In this paper, by monitoring cutting force and through the method of experimental research, grey theory, BP neural network and wavelet analysis etc., a tool wear on-line monitoring and prediction system which was developed by LABView and included modification of cutter and cutter head, cutting force signal monitored by wavelet analysis, tool wear prediction model based on grey theory GM (1,1), tool state recognition based on BP neural network and so forth is provided. The system had passed the test and proved to be effective.

2. Modification of Cutter and Cutter Head

2.1. Modification of Cutter
The cutter was modified by three-way piezoelectric force sensor and slip ring. The sensor was clipped between the cutter holder and the cutter bar. The device is showed in Fig.1. Note: 1-cutter bar 2-cutter holder 3-cutter pad 4-indexable insert tip 5-conical screw 6- three-way piezoelectric force sensor 7-connection bolt 8-cable.
2.2. Modification of Cutter Head

If there is relative rotation between cutter and cutter head, like whirlwind milling, the cutter head needs to be modified. The data transmission modes between two parts with relative rotation are slip ring contact, electromagnetic induction and wireless transmission. The mode of electromagnetic induction cannot meet the demand of high-speed data acquisition as Limit of the core frequency. Wireless data transmission mode has several type like radio type, infrared transmission type and optical fiber transmission type and the equipment cost of such data transmission is very high. The slip ring contact data transmission mode which is characterized by simple structure, low cost and suitable for data transmission between rotating parts at medium and low speed was adopted in this paper. As showed in Fig. 2, a multi-channel through-hole type slip ring was used as the interface between the sensor and the detection circuit. The connection of end of the slip ring rotor and the milling cutter head has feature of flange.

The cutting force of the modified tool was measured by a three-way piezoelectric force sensor, which is respectively connected with the cutter holder and the cutter rod thread. A multi-channel through-hole slip ring was used as the interface between the sensor and the detection circuit.

This measuring device has the characteristics of compact structure, good dynamic characteristics and easy to realize. It is suitable for on-line synchronous measurement of transient cutting force in cutting process.

Figure 1. Cutting force measuring device with cutter bar

Figure 2. Assembly and connection diagram of cutting sensing part with cutter head and slip ring
3. On-line Monitoring of Cutting Force Based on Wavelet and Neural Network

The cutter material of test in this paper was 40Cr with heat treatment T250 at size of 70×30×30. The size of the opening groove at the front end of the cutter bar was 26×30×20. Three-way pressure sensor we chose was Kistler9602A3, which was connected with cutter holder and cutter rod with M8 bolts.

The stepped hole diameter of the cutter bar was Φ 12mm, and the cutter bar can be adjusted by 5mm along the rod. The collected real-time cutting force signal was shown in Fig.3. The signal was decomposed into five layers of wavelet, as shown in Fig.4. The fifth layer of low-frequency coefficients was a5 and D1 to D5 were high-frequency coefficients of each layer obtained after wavelet decomposition. The relational expression of the original signal was \( s = a_5 + d_1 + d_2 + d_3 + d_4 + d_5 \).

The fifth low-frequency coefficient a5 which was obtained after wavelet packet decomposition of cutting force signal could clearly reflect the changing state of cutting force and realize the on-line monitoring of cutting force.

![Figure 3. Screenshot of real time cutting force](image)

![Figure 4. Cutting force screenshot of wavelet decomposition](image)

4. Cutting-tool Wear Prediction

4.1. Experimental Study on Cutting-tool Wear State

Three cutting-tools of the same specification but with wear amount at initial wear, slight wear and severe wear were used in the test. Through the three-dimensional piezoelectric force sensor installed on the cutting-tool, we used db5 wavelet to decompose cutting signal into five layers and obtained the corresponding fifth layer low frequency coefficient a5. See Fig.5, Fig.6, Fig.7.
Figure 5. the early worn tool

Figure 6. the slightly worn tool

Figure 7. the severely worn tool
4.2. Tool Wear Prediction Model Based on GM (1,1)

With the grey theory GM (1,1), we could predict resultant cutting force at time $t + 4 \Delta t$ by known resultant cutting force at four equal time interval.

Original cutting force $F^{(0)} = \{F^{(0)}(t)\}_{t=1,2,3,4} = \{F_1, F_2, F_3, F_4\}$.

The prediction model of cutting force was,

$$\hat{F}^{(1)}(t+1) = \hat{F}^{(1)}(t) + \hat{F}^{(1)}(t) = (F_1 - \frac{b}{a})\times (e^{-at} - e^{-a(t-1)})$$  (1)

In formula above, $t=0,1,2\ldots N$

The prediction value of $F^{(0)}(5)$ at time at $T+4\Delta t$ was,

$$\hat{F}^{(0)}(5) = (F_1 - \frac{b}{a})\times (e^{-4a} - e^{-3a})$$  (2)

The prediction model with grey theory cutter model was tested and verified and the test results are shown in Tab.1. It shows that the prediction accuracy of the model is high and the error is less than 5%.

### Table 1. Prediction of Cutting Force

| No. | Original Data | Actual | Prediction | Relative Error |
|-----|---------------|--------|------------|---------------|
| 1   | 810.37,857.54,863.71,915.68 | 914.11 | 937.67 | 2.58% |
| 2   | 857.54,863.71,915.68,914.11 | 928.58 | 950.81 | 2.39% |
| 3   | 863.71,915.68,914.11,928.58 | 949.67 | 931.93 | -1.87% |
| 4   | 915.68,914.11,928.58,949.67 | 1015.6 | 966.74 | 4.81% |
| 5   | 914.11,928.58,949.67,1015.6 | 1009.6 | 1054.1 | 4.41% |

4.3. Tool Wear State Recognition Based on BP Neural Network

We marked three types of tools at initial wear, slight wear and severe wear as A, B and C respectively. The corresponding relationship between cutting-tool state and target output of neural network was A: 1 0 0, B: 0 1 0, C: 0 0 1. The input layer of BP neural network is the eigenvector of A5 obtained by wavelet packet decomposition, and its dimension is 32. We set the number of hidden layer nodes at 18 and achieved the training target after 7 times of cyclic training, that is, the sum of error squares was within 0.0001. The well-trained BP neural network was tested and the test results are shown in Tab.2.

### Table 2. Recognition Results of Neural Network

| No. | Target expected output | Actual Output of Neural Network | Output Recognition |
|-----|------------------------|--------------------------------|--------------------|
| 1   | 1 0 0                  | 0.97472                        | 1 0 0              |
| 2   | 1 0 0                  | 0.94756                        | 1 0 0              |
| 3   | 0 1 0                  | 0.14692                        | 0 1 0              |
| 4   | 0 1 0                  | 0.16755                        | 0 1 0              |
| 5   | 0 0 1                  | 0.09022                        | 0 0 1              |
| 6   | 0 0 1                  | 0.08166                        | 0 0 1              |

The recognition results complete match the test samples that is two new tools, two slightly worn tools and two severely worn tools.
5. Development of Wear State Prediction Software of Cutting-tool
We integrated above functions with LabVIEW software and developed an on-line monitoring and prediction system for cutting-tool wear. It is shown in Fig.8 and Fig.9.

![Figure 8. Front panel of tool wear online monitoring and prediction system](image1)

![Figure 9. Front panel of tool wear status recognition system](image2)

6. Conclusion
The intelligent cutting-tool that developed in this project could be customized for different machine, different cutting-tools and cutter heads, also suits for processing methods that are difficult to be monitored online like whirlwind milling, etc., could realize the real-time monitoring and prediction of the stress and wear degree of cutting tools. In the future, with support of Internet technology, it can be used to realize remote transmission of tool online monitoring, timely adjustment or update through network, and would promote the intelligent of tools.

Acknowledgments
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