

Research on Tool Wear Detection Based on Genetic Neural Network

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Abstract. To improve the accuracy of tool wear detection, this paper proposes a tool wear detection method based on genetic neural network. Firstly, the vibration signals during tool processing are collected, and these signals are preprocessed to eliminate background noise. Then, in addition to the time-frequency analysis, the Ensemble Empirical Mode Decomposition which is more suitable for the processing of non-stationary random signals is also applied to extract tool wear sensitive features from signals. To reduce the computational complexity of the neural network, some minor components in the sensitive features can be omitted by kernel principal component analysis, leaving the principal components as the input of the neural network. Finally, aiming at the shortcomings of the BP neural network, the genetic algorithm is optimized in terms of chromosome coding, setting of control parameters and genetic operation, so that it can obtain better weights and thresholds to improve the BP neural network. The experimental result proves that the accuracy of BP neural network is 86.7% and that of genetic neural network is 96%. The tool wear detection method based on genetic neural network is more suitable for practical use.

1. Introduction

Tool wear is a common phenomenon in machining. Tool wear directly affects the efficiency and precision of machining. The detection of tool wear is one of the most important research directions in machining. It is of great significance in reducing machining cost and ensuring machining quality [1].

At present, tool wear detection technology generally includes three parts: signal acquisition, Signal Processing, and tool wear detection. Among them, tool wear detection as an important part has been widely concerned [2]. The signal generated by the process of machining is a time-varying signal. Therefore, the analytical method and empirical formula method used in the past have gradually failed to adapt to the complexity of the process of machining.

Artificial neural network is often used for tool wear detection due to its excellent performance in nonlinear modeling. Jakub Gajewski [3] uses discrete wavelet transform to extract tool wear characteristics. The state of the tool is classified by fuzzy neural network, and the recognition accuracy reaches 93.3%. Raphael Corne [4] aims to evaluate and analyse spindle power data for real-time tool wear monitoring. Power data spindle to feed into the neural network for functional processing. Zheng Jian ming [5] uses wavelet decomposition coefficient of power spectrum to fuse BP neural network to realize intelligent identification of the tool wear state. These studies usually use time-frequency analysis method, which is more suitable for the analysis of stationary and linear signals. In addition, the accuracy of tool wear detection by neural network is also insufficient, which cannot fully meet the requirements of actual use [6].



This paper analyses the current tool wear detection technology, and the vibration signal that can better characterize tool wear is selected for analysis. In addition to the time-frequency analysis, Ensemble Empirical Mode Decomposition is added to extract the characteristics of vibration signals. On the basis of Principal Component Analysis, the kernel function is introduced to make it more suitable for dimensionality reduction of tool wear characteristics. Aiming at the shortcomings of traditional BP neural network, the improved genetic algorithm is used to optimize its initial weight and threshold. Experiments show that the accuracy of tool wear detection by genetic neural network is up to 96%, which is more suitable for practical application.

2. Signal acquisition and processing

2.1. Vibration signal acquisition experiment

In this paper, VA3 vertical high-speed machining center is selected as the experimental platform to collect vibration signals. Install the acceleration sensor on the processing platform. As shown in figure 1, select the X, Y, Z three-axis direction to collect the vibration signal.

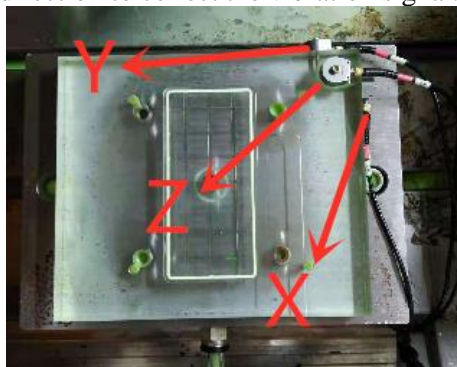


Figure 1. Acceleration sensor installation.

The size of processed workpiece is 100mm×40 mm×20mm. The material of processed workpiece is 316L stainless steel. The processing parameters are set as follows: $n=5000$ r/min, $V_c=1000$ r/min, $A_p=1$ mm, $A_e=5$ mm.

Keep the processing parameters unchanged, the single processing time is 4 seconds. After each processing, stop the machine to measure tool wear and record. After the tool and workpiece are completely cooled, repeat the above process. If the workpiece cannot be processed, replace the same one and continue until the tool is severely worn.

The vibration signals collected by the experiment, on the one hand, there are environmental disturbances in these signals, and on the other hand, the amount of data is too large. So it is impossible to input them directly into the neural network for use. The signal must be preprocessed to improve the signal-to-noise ratio. Then the sensitive characteristics of tool wear were extracted and screened. The preprocessing mainly uses smooth filtering to remove individual peak interference signals. These interferences mainly come from the vibration of other machines in the industrial environment or the vibration caused by human beings.

2.2. Signal processing

2.2.1. Characteristics extraction. Time-frequency analysis is a commonly used signal processing method, which is more suitable for the analysis of stationary signals. In this paper, the root mean square value, the main peak value of autocorrelation, Spectrum magnitude, Power spectral density and db1 Sub band energy are selected as the time-frequency characteristics of tool wear.

However, the vibration signal generated in the process of tool machining is non-stationary random signal. Therefore, in addition to the time-frequency analysis, the Ensemble Empirical Mode Decomposition (EEMD) [7] which is more suitable for the processing of non-stationary random

signals is also applied in this paper. To solve the modal aliasing problem of Empirical Mode Decomposition (EMD), EEMD emerge as the times require. It is an adaptive time-frequency localization analysis method, which gets rid of the limitations of Fourier transform. Unlike the wavelet packet transform, it does not need to set the basis function.

The steps of EEMD are as follows:

1) Gaussian White noise is added to the original signal for several times to obtain the signal with white noise added for the i th time.

$$S_i(t) = S(t) + n_i(t) \quad (1)$$

2) EMD was performed on all the obtained $S_i(t)$.

$$S_i(t) = \sum_{j=1}^n c_{ij}(t) + r_{in} \quad (2)$$

Where $c_{ij}(t)$ describes the IMF component while r_{in} represents the residual component.

3) The overall average of all IMF components is calculated to obtain the final IMF.

$$c_i(t) = \frac{1}{N} \sum_{i=1}^N c_{in}(t) \quad (3)$$

After multiple debugging, when the standard deviation of Gaussian white noise is 0.3 and the number of noise addition is 100, the effect of EEMD is the best.

2.2.2. Characteristics Selection. The tool wear sensitive characteristics extracted by time-frequency analysis and EEMD, many of which have high dimension. In order to further reduce the computational complexity of the neural network, some components with small contribution rate can be eliminated from the characteristics.

Kernel function principal component analysis (KPCA) [8] is a nonlinear expansion algorithm of principal component analysis (PCA), which extracts principal components by non-linear methods. KPCA maps the original data to high-dimensional space by the mapping function before PCA. KPCA can remove the secondary characteristics and noises from the high dimension tool wear sensitive characteristics, and retain the main components, so as to improve the data processing speed.

The steps of KPCA are as follows:

1) Signal sample data is constructed by gaussian radial basis function.

2) Calculate the eigenvectors and eigenvalues of the kernel function matrix. Find the contribution rate of the elements corresponding to each eigenvalue (the ratio of each eigenvalue to the sum of all eigenvalues).

3) The cumulative contribution rate is set to 95%, and the first six principal components are taken to reflect the original information.

Finally, the six principal components contain more than 95% of the original sensitive characteristics, which greatly reduce the complexity and increase the speed of the operation.

3. Genetic neural network

BP neural network (BPNN) [9] is a kind of multilayer feedforward network trained by error back propagation. It uses gradient search technology to minimize the mean square error between the actual output and the desired output. BPNN has strong nonlinear mapping ability and adaptive ability. At the same time, it also has a good performance in fault tolerance.

However, BPNN also has some shortcomings. The essence of BPNN is a local search algorithm, which does not have the ability of global search. In addition, due to the complexity of tool wear detection, BPNN has insufficient ability to deal with it.

As an important branch of artificial intelligence, genetic algorithm (GA) [10] is an optimization mechanism based on natural selection and biological genetic mechanism abstracted from biological evolution process. It solves the problem according to the natural evolutionary rules of the survival of the fittest. It has good scalability and is easy to integrate with BPNN.

The sample genetic algorithm (SGA) has two major shortcomings. The first one is that the algorithm has limited ability to explore new space, which makes it easy to converge to the local optimal solution. The other is that the algorithm will swing around the optimal solution, making it difficult to converge. In view of these shortcomings of SGA, this paper improves it in chromosome

coding, setting of control parameters and genetic operation so it can better optimize BPNN. The algorithm flowchart of BPNN optimized by improved genetic algorithm (IGA) is shown in figure 2.

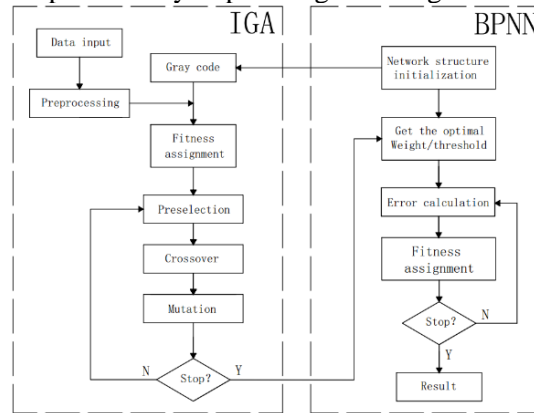


Figure 2. Algorithm flowchart.

The SGA adopts binary coding, but it has the problem of Hamming cliff. In the gray code corresponding to two consecutive integers, only one bit is different. Therefore, when variation occurs, its original phenotype is continuous with its present phenotype. Gray code can effectively solve the problem of Hamming cliff and improve the local search ability of SGA.

In the setting of control parameters, the SGA adopts fixed crossover probability and mutation probability. It means that individuals with good or inferior quality have undergone the same probability of crossover and mutation operations. This paper introduces the idea of self-adaptation [11]. At the initial stage of evolution, the population needs a high probability of crossover and mutation in order to find the optimal solution quickly. However, at the later stage of evolution, the population needs low probability of crossover and mutation to converge quickly after finding the optimal solution. The probability of crossover and mutation needs to be adjusted with the evolution of population to meet the needs of evolution.

Compared with the linear function used in the adaptive genetic algorithm, sigmoid function has a smoother top and bottom. This function shows a good balance between linear and nonlinear changes. It is more suitable for adaptive adjustment of crossover probability and mutation probability. The adaptive adjustment formulas for crossover probability and mutation probability are shown in equations (1) and (2). Where f_{\max} represents the maximum fitness of the population and f_{avg} represents the average fitness of the population.

$$P_c = \begin{cases} \frac{K_1 - K_2}{1 + \exp\left(A \left(\frac{2(f_c - f_{\text{avg}})}{f_{\max} - f_{\text{avg}}}\right)\right)} + K_2 & f_c \gg f_{\text{avg}} \\ K_1 & f_c \ll f_{\text{avg}} \end{cases} \quad (4)$$

Where f_c represents the greater fitness of the two individuals participating in the crossover. K_1 represents the maximum crossover rate and k_2 represents the minimum crossover rate.

$$P_m = \begin{cases} \frac{K_3 - K_4}{1 + \exp\left(A \left(\frac{2(f_m - f_{\text{avg}})}{f_{\max} - f_{\text{avg}}}\right)\right)} + K_4 & f_m \gg f_{\text{avg}} \\ K_3 & f_m \ll f_{\text{avg}} \end{cases} \quad (5)$$

Where f_m represents the fitness of the mutant individual. K_3 represents the maximum mutation rate and k_4 represents the minimum mutation rate.

The adjustment curves of crossover probability and mutation probability are shown in figure 3 and figure 4.

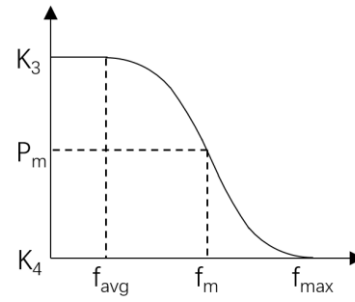
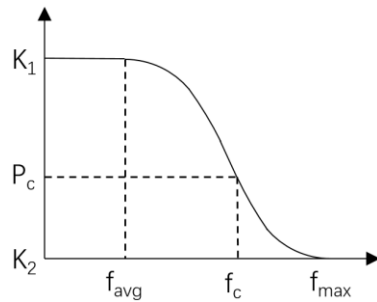


Figure 3. Cross probability adjustment curve. Figure 4. Mutation probability adaptive curve.

In the genetic operation, the preselection strategy is used to improve the selection operation [12]. When the fitness of the new generation is greater than that of the parent, the new generation will inherit to the next generation instead of the parent, otherwise the parent will be retained.

As shown in Figure 5, the fitness value of IGA is reduced to the lowest when the evolutionary generation is 4, which improves its convergence speed. The prediction error comparison between BPNN and IGA-BP is shown in Figure 6. It can be seen that compared with BPNN, IGA-BP has significantly improved the prediction ability.

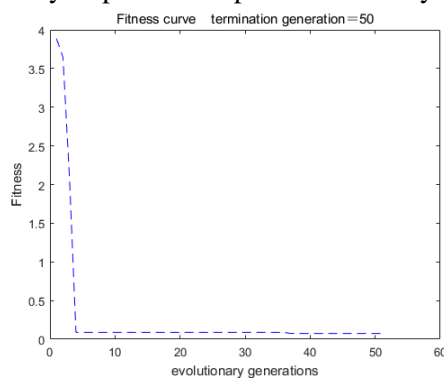


Figure 5. Fitness curve of IGA.

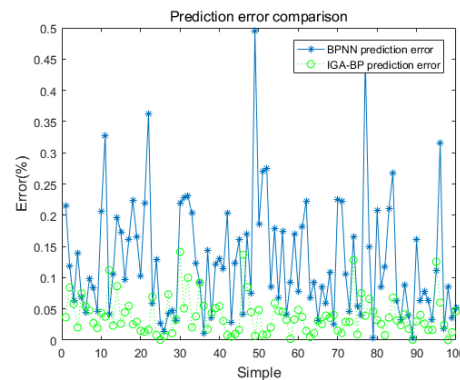


Figure 6. Prediction error.

4. Results and analysis

The output of the neural network (tool wear) is normalized to [0, 1]. The five tool wear states are set as follows: new tool state [0, 0.1], initial tool wear state [0.1, 0.3], medium tool wear state [0.3, 0.6], late tool wear state [0.6, 0.9], and severe tool wear state [0.9, 1].

The experimental data were trained by BPNN and IGA-BP respectively. 30 groups of test data corresponding to five tool wear states were randomly selected for verification. The results are shown in table 1 and table 2.

Table 1. Result of BPNN.

No.	Actual wear state	Correct identification	Accuracy rate
1	new tool state	28	93.3%
2	initial tool wear state	26	86.7%
3	medium tool wear state	23	76.7%
4	late tool wear state	24	80%
5	severe tool wear state	29	96.7%

Table 2. Result of IGA-BP.

No.	Actual wear state	Correct identification	Accuracy rate
1	new tool state	30	100%
2	initial tool wear state	29	96.7%
3	medium tool wear state	27	90%
4	late tool wear state	28	93.3%
5	severe tool wear state	30	100%

As can be seen from the table, when using BPNN for detection, only the new tool state and severe wear state have an accuracy rate of over 90%. The detection accuracy for the medium tool wear state is even less than 80%. The overall average accuracy of the five tool wear states is only 86.7%.

However, the IGA-BP has a detection accuracy of 100% for the new tool state and the severe tool wear state. The accuracy of others is also above 90%. The overall average accuracy rate reached 96%. Compared to the BPNN, the accuracy of tool wear detection has increased by nearly 10%.

5. Conclusion

To improve the accuracy of tool wear detection, this paper takes the tool processing process as the experimental basis and collects the vibration signal. To reduce the computational complexity of the neural network, time-frequency analysis and the EEMD are performed to extract tool wear sensitive characteristics. The KPCA is then used to extract the principal components of the sensitive characteristics for training and testing of BPNN and IGA-BP. The experimental results show that the accuracy of tool wear detection of IGA-BP is up to 96%, which is significantly improved compared with the traditional BPNN. It provides a good theoretical basis for further research on tool wear condition monitoring and makes it more suitable for practical use.

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