A Review of Monitoring Methods for Tool Wear

Lijie Yang[a], Liqiang Wang[b] and Bo Shi[c]

Tianjin University of Technology and Education, Tianjin 300222, China

[a]0422211027@tute.edu.cn, [b]wangliqiang@tute.edu.cn, [c]2468237609@qq.com

Abstract

As a necessary tool in machining, tool wear is inevitable during milling. Therefore, developing reliable and convenient methods to predict the wear state of tools in industrial production and processing is of great significance in terms of improving productivity, reducing production costs, and maintaining the quality of workpiece. Traditional tool wear prediction methods can be categorized into direct prediction and indirect prediction based on the type of wear information obtained.With advancements in machinery manufacturing automation, rapid developments in sensor technology and control theory, and continuous updates and changes in tool wear state technologies, this paper reviews recent detection methods for tool wear. Specifically, it focuses on analyzing sensor selection for signal acquisition and intelligent diagnosis based on deep learning algorithms. Finally, the application status and shortcomings of tool wear detection are discussed in order to promote progress and development in tool wear detection technology.

Keywords

Tool Wear; Intelligent Detection; Signal Acquisition; Deep Learning Algorithms.

1. Introduction

Since the 21st century, China's manufacturing industry has been in a stage of vigorous development, and in 2015 the "Made in China 2025" strategic plan was promulgated, the core of which is to accelerate the development of the intelligent level of the manufacturing industry, so that information technology and manufacturing integration and complementarity[1]. In the contemporary manufacturing system, in order to ensure the high performance of the automated machining process and the surface quality of the machined workpiece, real-time prediction of the state of the tool is an urgent problem to be solved in the machining process.

In the current mechanical automation production process, CNC machine tools are widely used in the manufacturing industry because of their superior reliability and high processing efficiency, tools as an important basic component of machine tools, is the most core tool of machine tool milling processing, and the component is also the most wasted and the most lost [2]. Tool milling processing is a rather cumbersome process, in this process, the tool must always interact with the workpiece, the two will be fierce friction resulting in high pressure and high temperature, which will cause different degrees of damage to the tool, when the tool is lightly worn, the surface quality of the machining workpiece will be reduced, and when the degree of tool wear is large, the work of the entire machine tool will be deleyed, and even lead to safety problems. As early as 1990, a survey showed that an average of 6.8% of downtime was caused by tool failure, and with the incre-ase in the degree of automation in the manufacturing environment, its proportion quickly rose to 20%; In addition, with the rapid development of CNC machining, relevant studies have shown that the downtime of CNC untimely tool replacement accounts for 20%-30% of the total downtime was caused by machine tools[3[4]. Therefore, in the process of mechanical production and processing, in

ISSN: 2414-1895 DOI: 10.6919/ICJE.202305_9(5).0055

order to ensure the quality of the processed workpiece, improve the safety of production and processing, and reduce the production cost, it is of great research significance to predict the wear status of the tool in time.

2. Traditional Tool Wear State Prediction Method

With the changes of the times, the research of tool wear prediction method has been more than 30 years, in these years of research, with the continuous improvement of the degree of automation of mechanical manufacturing, the rapid development of sensor technology and control theory, tool wear state technology is constantly updated[5][6]. At present, the tool wear prediction methods that can be realized can be divided into direct prediction method and indirect prediction method according to the different tool wear information obtained[7].

2.1 Direct Prediction Method

Direct prediction method is an offline method, with the continuous milling of the tool, the cutting edge surface state and tool shape will produce different wear changes, by directly observing several changes of the tool, and then predict the tool wear state, this method is called direct prediction method.

The commonly used direct prediction methods are as follows : mechanical measurement method, tool workpiece spacing measurement method, optical projection method and computer image processing method[8]. The mechanical measuring method is to use some measuring tools to directly measure the tool itself in an all-round way; Tool workpiece spacing measurement method is the use of some instruments to measure the distance between the tool and the workpiece, although the method has high precision, but it is susceptible to environmental interference, the workpiece shape, workpiece surface quality and other changes are more sensitive; The optical projection method is to enlarge the image of the tool wear part by optical principle, and then project it to the screen, measure the image on the screen, and finally obtain the size of the tool wear part after the relevant conversion; Computer image processing method is through the light source and CCD camera to collect the image of tool wear, and transmit to the computer, the use of computer to achieve accurate measurement of the tool wear state, the method of measurement accuracy and no contact, no wear, currently only for laboratory testing.

2.2 Indirect Forecasting Method

In today's era of efficiency and detail, indirect prediction can well meet the requirements of mechanical milling processing under high automation. Compared with the direct prediction method, the indirect prediction method is cheaper, more efficient and less subject to on-site disturbances, making it more suitable for industrial milling.

Tool indirect prediction method refers to the acquisition of dynamic signals in tool milling processing through sensors, according to the different signals collected by different sensors, the characteristic values closely related to the tool wear state are extracted in these signals, and the wear state of the tool is predicted by these feature values. It mainly consists of two stages, the first stage is model training and the second stage is online prediction. The first step of model training includes obtaining various information of the tool in cutting processing through various sensors, obtaining training samples, and then passing through signal processing, information extraction, data fusion and pattern recognition, and finally training and optimization to obtain a tool wear prediction model. Simply put, it is a pattern state recognition process, and the model training construction structure is shown in Figure 1 below. The second step is to use the trained predictive model to achieve real-time online prediction of the tool.

Indirect prediction methods commonly used include vibration detection, cutting force detection, current signal measurement, acoustic emission detection, etc.[9]. The cutting force detection method can judge the wear state of the tool according to the change of cutting force. Its advantages are that the cutting force signal has strong anti-interference ability and the signal contains a lot of information related to tool wear, but it is only suitable for precision machining with special needs. The vibration

 Volume 9 Issue 5, 2023
DOI: 10.6919/ICJE.202305_9(5).0055

detection method will increase with the wear of the tool, and its amplitude will change accordingly, and its advantages are lower cost, easy installation and high reliability, but the signal strength collected by different installation positions is different; The current signal measurement method uses the spindle power of the machine tool or the current of the induction motor to analyze and judge the tool wear, so as to realize the online prediction of the tool. Its advantages are convenient signal acquisition, reliable information, low price and not affected by the environment, but it cannot quantify the tool wear-related characteristics contained in the signal; The acoustic emission detection method is that during the milling process of the machined workpiece, the acoustic emission sensor can collect the breaking wave to diagnose the wear state of the tool. The advantage of this method is that it has high sensitivity and will not affect the milling process, but the sampling frequency of this method is too high, which will lead to troublesome data processing and retention, and is suitable for high-end machine tools and laboratory research.Intelligent identification and diagnosis of tool wear.

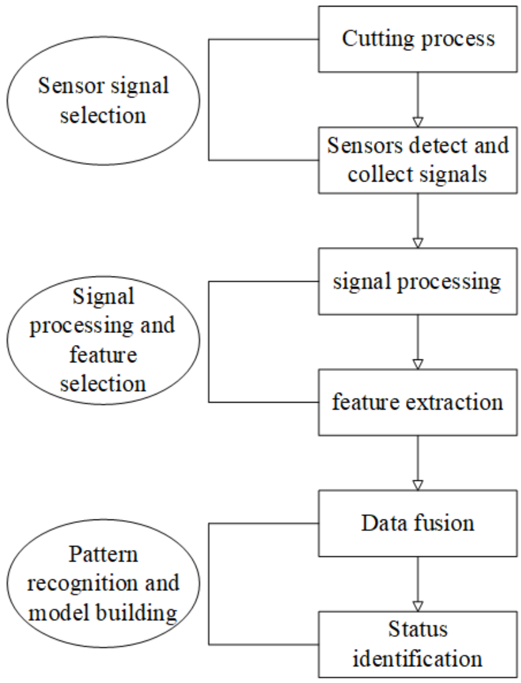

Fig 1. Tool wear prediction flowchart

3. Intelligent Identification and Diagnosis of Tool Wear

3.1 Tool Wear Form and Wear Prediction

The wear forms of the tool include rake face wear, flank wear and boundary wear. Rake face wear mainly occurs in the process of cutting plastic materials, often due to the large degree of cutting, resulting in grinding crescent puddles on the rake face. The wear of the flank face of the tool is due to the strong friction between the flank face and the workpiece surface, resulting in the flank face gradually wear into a prism with zero back angle. The boundary wear of the tool often occurs during the cutting of steel, and wear occurs at the part of the main cutting edge close to the outer skin of the workpiece and deep grooves appear.

Over the years, many domestic and foreign scholars have directly observed the state of the tool to predict the wear state of the tool and study it. Shao-Hsien Chen et al. studied the correlation between the color change of the chip surface of the tool and the tool wear, and based on this, proposed a system that relies on the chip color generated in the cutting process to predict the tool wear, and the experimental results show that the system can accurately and quickly predict the tool wear[9]. Xu Luyan, Qiu Zhongjun and others from Tianjin University successfully constructed an image online acquisition system through research and design, and successfully used the system to obtain relevant images of tool wear, and then calculated the matching degree of the tool wear image obtained online and the original tool wear image to judge the tool, and the experimental results show that the tool prediction system based on the shape template mapping algorithm has good stability[10].

3.2 Use Sensor Information for Predictive Identification

Milling of machine tools is a complex and continuous physical process, in order to predict the tool through sensor information, it is necessary to select a reliable sensor, but also to consider the suitability of the sensor, anti-interference, price conditions, etc.

In terms of sensor selection, K. Venkata Rao et al. used laser Doppler vibrometer to collect workpiece vibration data online, and used artificial neural network to predict tool wear, and the surface vibration signal of the test results can be well used to predict tool wear[11]; Daniel Frank Hesser et al. used the acceleration data collected by the acceleration sensor to analyze the tool state, and finally successfully classified different tools[12]; D. Rajeev et al. measured the change of cutting force during hard cutting, and proposed a tool wear estimator based on neural network, and the experimental results show that the estimator can be used for online estimation of tool wear[13]; Mehrdad Nouri Khajavi et al. established a correlation model between motor current and tool wear state that can be used to predict tool wear, and the final results prove that the designed tool wear prediction system has good performance[14]; Zhixiong Li et al. considered that it was difficult to install some sensors in the actual factory, selected the inexpensive and convenient audio signal for factory installation as the prediction signal, and used the collected experimental data to develop and verify the prediction model, and finally proved that the prediction model can classify the tool wear with high precision and can be applied to actual industrial production[15]; Boya Niu et al. collected cutting force, vibration and cutting sound as prediction signals and developed a variety of support vector machines (SVM) is used to fuse multi-sensor signals and identify the wear stage of cutting tools, and also studies the tool wear prediction performance based on single force sensor and vibration sensor, and the final results show that the recognition accuracy of multiple sensors is better than that of a single sensor[16].

3.3 Tool Wear Signal Feature Extraction

The signal collected by the sensor, although it contains a lot of tool wear related information, but also contains a lot of interference information, so it is necessary to carry out a series of preprocessing of the collected signal, usually using amplification, filtering and other operations to filter out some background noise and interference information, and then conduct more in-depth exploration and research on the preprocessed signal to find the characteristic values related to tool wear.

In terms of signal processing and tool eigenvalue research, Meng Hu et al. obtained the cutting force and acoustic emission signal in titanium alloy tool cutting, extracted time-domain statistical features such as maximum, variance and kurtosis, and then used linear discriminant analysis (LDA) to reduce the dimensionality and find the best data set for training, and finally, applied the +-support vector machine (+-SVM) to training and prediction[17]; In the frequency domain, Ku Xiangchen et al. realized the mapping relationship between the two by analyzing the vibration signal during tool turning, using the frequency amplitude within a certain spectrum range as the input of the BP neural network, and successfully identifying and predicting the tool wear[18]. In the time-frequency domain, Sarvesh Kumar Mishra et al. studied the applicability of fast Fourier transform (FFT) and discrete wavelet transform (DWT) in the analysis of tool milling machining signals, and finally the test result surface, at higher cutting speeds, compared with FFT, wavelet transform can analyze the signal in more detail, and is faster and more effective[19]; Based on continuous wavelet transform (CWT) and blind source separation (BSS) technology, Tarak Benkedjouh et al. proposed a new intelligent method for predicting tool wear state, and the experimental results surface, the proposed CWT-BSS method can effectively reflect the wear state of cutting tools in the milling process[20].

3.4 Intelligent Diagnosis based on Deep Learning Algorithm

After the analysis, selection and tool wear have associated feature values, if only relying on these feature values, it is not possible to identify and predict the tool, and it is also necessary to establish a system model to represent the feature value and tool wear state as a function, and finally use the model to achieve real-time prediction of the tool.

In terms of tool wear prediction model, Juraj Kundrík et al. introduced how to realize tool wear prediction through neural networks based on vibration and cutting force measurements[21]; Premnath et al. studied the comparison of artificial neural network (ANN) and the study of reaction surface method (RSM) in the modeling and prediction of tool wear during milling, and the comparison results show that the artificial neural network model outperforms the RSM model and provides more accurate prediction of tool wear[22]. Guofeng Wang et al. proposed a Gaussian mixed regression (GMR) model, which also used multilinear regression, radius basis function and loopback neural network to compare with the GMR model, and the analysis of the four performance criteria showed that the GMR-based method was the most accurate among these methods[23]; Taking into account the superior capabilities of the hidden Markov model (HMM) in modeling non-stationary physical processes, Weijian Li et al. developed an improved hidden Markov model for tool wear monitoring under switch cutting conditions of micromilling[24].

4. The Bottleneck of the Current Tool Wear Prediction Technology

The milling process of CNC machine tools is a very cumbersome and changeable process, and the prediction of tools is a very complex problem. The bottlenecks and main problems it faces are also as follows:

Sensor selection. CNC machine tools because of their internal complexity, in order to really apply the sensor to industrial production and processing, it is inevitable to be affected by the difference in CNC machine tools, installation environment differences, processing conditions changes and other factors, such as high reliability of cutting force sensors, if to be applied to industry, the installation requirements are higher, often need to adjust the machine tool structure, resulting in its low versatility.

Signal analysis and feature extraction. In a complete tool wear prediction system, the signal obtained by the sensor contains a large amount of irrelevant information, and the amount of data is large, in order to accurately extract the most representative tool wear related information, it is necessary to conduct a deeper study on the theory of signal processing technology, and the acquisition of feature value samples also needs to consider how to use fewer feature value samples in line with the processing reality to obtain a high-accuracy tool wear state prediction model, thereby reducing the time and cost of tool prediction system construction.

Timeliness. Tool wear prediction system from the signal input collected by the sensor to the output of the prediction model, this process is accompanied by complex signal processing and more mathematical models, and real-time prediction requires a high response speed, which requires the best optimization ability of the entire system, the use of the latest intelligent algorithms to improve the efficiency of the entire system.

References

[1] Sun, Y.N. and Bai, X.J. Made in China 2025: A Strong Nation Strategy with Chinese Characteristics, Intelligent Manufacturing, vol. 10 (2020), 43-45. (In Chinese)

[2] Zhou, Y.Q. Research on State Monitoring and Remaining Effective Life Prediction Method of Upright Milling Cutter. (Zhejiang University of Technology, 2020), p. 2-3. (In Chinese)

[3] Li, D. and Mathew, J. Tool wear and failure monitoring techniques for turning-a review. International Journal of Machine Tools and Manufacture, Vol. 30 (1990) No. 4, p. 579-578.

[4] Vetrichelvan, G., Sundaram, S., Kumaran, S.S. and Velmurugan, P. An investigation of tool wear using acoustic emission and genetic algorithm. Journal of Vibration and Control, Vol. 21 (2015) No. 15, p. 3061-3066.

[5] Tlusty, J. and Andrews, G.C. A Critical Review of Sensors for Unmanned Machining. CIRP Annals - Manufacturing Technology, Vol. 32 (1983) No. 2, p. 563-572.

[6] Kurada, S. and Bradley, C. A review of machine vision sensors for tool condition monitoring. Journal of Materials Processing Technology, Vol. 34 (1997) No. 1, p. 55-72.

[7] Guo, J.C. and Li, A.H. Research Progress of Tool Wear State Monitoring Technology. Tool Engineering, Vol. 53 (2019) No. 5, p. 3-13. (In Chinese)

[8] Wang, D. and Yang, L. Principle of Tool Wear and Detection Method of Tool Wear. Farm Machinery Use and Maintenance, vol. 11 (2018), 24-25. (In Chinese)

[9] Chen, S.H. and Luo, Z.R. Study of Using Cutting Chip Color to the Tool Wear Prediction. The International Journal of Advanced Manufacturing Technology, Vol. 109 (2020), No. 3-4, p. 823-839.

[10] Xu, L.Y. and Qiu, Z.J. Research on In-Machine Monitoring Method for Cutting Tools Based on Shape Matching. Nanotechnology and Precision Engineering, Vol. 15 (2017), No. 5, p. 419-424. (In Chinese)

[11] Rao, K.V., Murthy, B.S.N. and Rao, N.M. Prediction of cutting tool wear, surface roughness and vibration of workpiece in boring of AISI 316 steel with artificial neural network. Measurement, vol. 51 (2014), 63-70.

[12] Hesser, D.F. and Markert, B. Tool wear monitoring of a retrofitted CNC milling machine using artificial neural networks. Manufacturing Letters, vol. 11 (2018), 43-48.

[13] Rajeev, D., Dinakaran, D. and Singh, S.C.E. Artificial neural network-based tool wear estimation on dry hard turning processes of AISI4140 steel using coated carbide tool. Journal of Mechanical Science and Technology, Vol. 65 (2017), No. 4, p. 553-559.

[14] Khajavi, M.N., Nasernia, E. and Rostaghi, M. Milling tool wear diagnosis by feed motor current signal using an artificial neural network. Journal of Vibroengineering, Vol. 30 (2016), No. 11, p. 4869-4875.

[15] Li, Z., Liu, R. and Wu, D. Data-driven smart manufacturing: Tool wear monitoring with audio signals and machine learning. Journal of Manufacturing Systems, vol. 48 (2019), 66-76.

[16] Niu, B., Sun, J. and Yang, B. Multisensory based tool wear monitoring for practical applications in milling of titanium alloy. Measurement, Vol. 22 (2020) No. 3, p. 1209-1217.

[17] Meng Hu, Weiwei Ming, Qinglong An. Tool wear monitoring in milling of titanium alloy Ti–6Al–4 V under MQL conditions based on a new tool wear categorization method. Wear, Vol. 104 (2019) No. 9-12, p. 4117-4128.

[18] Ku, X., Guo, Y., Duan, M., & Cao, B. Prediction of tool wear using vibration spectrum. Machinery Design and Manufacture, vol. 10 (2017), 113-116. (In Chinese)

[19] Mishra, S. K., Rao, U. S., & Kumar, S. Tool wear prediction by using wavelet transform. International Journal of Machining and Machinability of Materials, Vol. 6 (2016) No. 3/4, p. 216-230.

[20] Benkedjouh, T., Zerhouni, N., & Rechak, S. Tool wear condition monitoring based on continuous wavelet transform and blind source separation. Wear, Vol. 97 (2018) No. 9-12, p. 3311-3323.

[21] Kundrík, J., Kočiško, M., Pollák, M., et al. Use of Neural Networks in Tool Wear Prediction. Procedia Manufacturing, Vol. 299 (2019), p. 174-179.

[22] Premnath, A., Alwarsamy, T., & Sugapriya, R. A comparative analysis of tool wear prediction using response surface methodology and artificial neural networks. Engineering Science and Technology, an International Journal, Vol. 12 (2014) No. 1, p. 38-48.

[23] Wang, G., Qian, L., & Guo, Z. Continuous tool wear prediction based on Gaussian mixture regression model. Journal of Materials Processing Technology, Vol. 66 (2013) No. 9-12, p. 1921-1929.

[24] Li, W., & Liu, T. Time varying and condition adaptive hidden Markov model for tool wear state estimation and remaining useful life prediction in micro-milling. Journal of Manufacturing Systems, Vol. 131 (2019), 689-702.