

Research Progress on Monitoring of CNC Machine Cutting Tools Wear Condition

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Abstract: This paper analyzes the current situation cutting tools wear monitoring technology of CNC machine at home and abroad, analyzes the cutting tools wear monitoring technology deficiency based acoustic emission, vibration, cutting sound, motor current, cutting force. The application prospect of laser Doppler vibration measurement technology in CNC machine cutting tools wear monitoring is researched.

Keywords: CNC machine, cutting tools wear monitoring, laser Doppler vibrometer

1. Introduction

During the actual production process, it is difficult to accurately determine the cutting tools true wear state of the machine in use, and then provide accurate information for replace the cutting tools in the process of CNC machine operation. At the present stage, the cutting tools automatic change technology of CNC machine is relatively mature, what we lack is the accurate judgment of cutting tools use status. Inaccurate judgment will have the following effects in manufacture. If the cutting tools wear judgment is early (in fact, it is not completely worn) and the cutting tools is replaced, there will be the waste of cutting tools and great economic losses. If the cutting tools wear judgment is lagged behind (the cutting tools is completely worn, it is over-use), there will be influence of the quality of processed products, which will lead to serious phenomena such as processing is not in place and product scrapping.

The following hot and difficult problems exist in theoretical research and application research. Firstly, we have to find out a method which is scientific and can also accurately judge the real-time use status of cutting tools wear of CNC machine. Then, we form a practical design scheme of cutting tools replacement system. This paper reviews the research status of the monitoring of cutting tools wear in the machining process of CNC machine at home and abroad, the focus of this paper is the research in this field in China, then gives prospects for the use of laser Doppler vibrometer, which is used in monitor cutting tools wear.

2. Research on Cutting Tools Wear Monitoring Technology of CNC Machine

The research on cutting tools wear monitoring technology of CNC machine tools started early. The mainstream research method at home and abroad is to realize cutting tools wear monitoring by monitoring the sensor signals related to cutting tools wear or damage. Monitoring signals mainly include acoustic emission, vibration, cutting sound, motor current, cutting force, etc., as well as a variety of monitoring information fusion.

2.1. Overview of Foreign Situation

Kistler Company of Switzerland has launched a series of piezoelectric rotary dynamometers, which can be used in milling and drilling, and used in four dimensional force measurement of spindle with

speed up to 20000rpm[1].

Totis G et al. integrated a Kistler three dimensional force sensor behind each cutting tools tooth of the milling cutting tools to measure the three dimensional cutting force received by each cutting tools tooth in the milling process[2].

Based on PVDF piezoelectric film sensor, Lei Ma and his partner of Georgia Institute of technology developed a low cost sensing cutting tools handle that can measure radial force and torque in two directions. By arranging three PVDF piezoelectric around the cutting tools rod, the X and Y forces in the milling process can be measured[3].

Based on the strain force sensor, Pro-micron Company of Germany has developed SPIKE series (Sensory Tool Holder), which can not only measure the information of axial force, torque and two-way bending moment, but also measure the temperature information in the cutting process. It is suitable for the measurement of force and other information when the spindle speed is up to 18000rpm[4].

Ryo Matsuda et al. in Japan integrated an acceleration sensor on the milling tool handle and embedded a micro thermocouple at the tool tip to realize the simultaneous acquisition of cutting vibration and cutting temperature signals[5].

2.2. Overview of Domestic Research

Based on multi-feature analysis of acoustic emission signals, Guan Shan and his partner studied the prediction of cutting tools wear under change cutting conditions. According to the cutting experimental data, empirical mode decomposition, high order spectral analysis and wavelet transform are introduced into cutting tools wear feature extraction, and a cutting tools wear prediction method based on multifractal detrended wave analysis and least squares support vector machine acoustic emission signal multi feature analysis and fusion is proposed. They used MF-DFA (Multifractal detrended Analysis) to process the acoustic emission signals of cutting tools wear after denoising, the changes of multifractal spectrum parameters in different wear stages are analyzed, and the multifractal spectrum parameters that can sensitively represent the tool wear state are selected. The tool-wear status recognition is performed using the LS-SVM (Least Square Support Vector Machine) algorithm, the support vector machine algorithm and the neural network algorithm are compared to the cutting tools wear status identification, and the cutting tools wear monitoring system based on digital signal processing is developed. This system has a high-speed USB interface, which can upload the field data to the computer in time for data processing, and realize the monitoring cutting tools wear state under different machining methods. The system has strong universality, and can be used to monitor the cutting tools condition of any machining method in theory. The developed cutting tools wear monitoring system can realize the prediction and alarm of cutting tools wear 10s in advance[6,7].

In addition, Guan shan et al. invented an algorithm based on image features and linear local tangent space alignment(LLTSA)to realize the monitoring of cutting tools wear status [8]. Firstly, the acoustic emission sensor is used to collect the acoustic emission signals during cutting, and the ensemble empirical mode decomposition(EEMD) algorithm is used to denoise the signals. Secondly, the S transform is used to analyze the noise reduction signal in time and frequency, and the time-frequency image is converted into contour gray map. The texture features of the image are extracted by gray level co-occurrence matrix algorithm, and then the extracted feature vectors are reduced in dimension and optimized by scatter matrix and LLTSA algorithm to obtain fused feature vectors. Finally, the discrete hidden Markov model of cutting tools wear status is trained by fusing feature vectors, and a classifier is established, so as to realize automatic monitoring and recognition of tool wear status. The method combines three processes of “signal noise reduction”, “feature extraction and optimization” and “pattern recognition” to realize the monitoring of cutting tools wear status. However, its recognition accuracy and real-time performance are not described in detail in reference [8].

Zhang Kaifeng et al. chose acoustic emission sensor, microphones and current sensors as monitoring sensors for cutting tools wear status. Acoustic emission signal, cutting sound signal and current signal of machine cutting tools spindle motor are collected by orthogonal experiment. According to the characteristics of each sensor signal, different methods are selected for signal filtering and feature value extraction. For acoustic emission signals, wavelet packet transform is used to filter, and generalized fractal dimension method is used to extract generalized fractal dimension features of signals. For cutting acoustic signals, empirical mode decomposition method is used to filter, and Hilbert-Huang transform is used to extract signal features. For current signal, the wavelet packet transform method is used to construct the time-frequency matrix of wavelet packet reconstruction

coefficient, and the energy feature and singular value feature of wavelet packet are extracted by using this matrix. By comparing and analyzing support vector machine(SVM) with BP neural network and fuzzy neural network (FNN), the support vector machine model with better overall performance is selected as the feature layer fusion model of multi-sensor information and the decision layer fusion model to monitor the cutting tools wear status. By building an integrated model and designing an effective fusion method, the decision level fusion of multi-sensor information is realized. The fusion effect of different types of monitoring signals in decision-making layer is analyzed, and the monitoring effect of decision-making layer fusion is compared with that of using a single type of monitoring signal. It is proved that the fusion method of decision-making layer can realize the information complementation among different types of monitoring signals, The monitoring accuracy and reliability of the system have been improved by the decision making level fusion of multi-sensor information [9].

Chen Hongtao studied the identification and prediction of cutting tools wear state based on multi-parameter information fusion[10], and designed the test scheme. The life cycle information of cutting force, vibration, acoustic emission and cutting temperature in NC lathe work under different cutting conditions is collected in real time, and the total empirical mode decomposition (J-EEMD) algorithm under approximate joint diagonalization is adopted to extract the features of tool wear state. On the basis of neural network pattern recognition, the support vector machine algorithm is applied to identify the cutting tools wear status twice. Experimental results show that this method has good recognition rate and robustness.

Dong Hui selected acoustic emission signals as monitoring signals. used HHT(Hilbert-Huang Transform) analysis technology, combined with the best wavelet packet filtering pretreatment to monitor the cutting tools wear state, and selected the least squares support vector machine to identify the cutting tools wear state[11].

Nie Peng et al. developed a cutting tools tester [12], which includes acoustic emission sensor, preamplifier, signal conditioning module, signal processing module and display control module. The acoustic emission sensor is adsorbed on the cutting tools holder through the magnet of the housing, and its output end is connected to the preamplifier. The preamplifier is connected to the signal conditioning module by a signal cable, the output of the signal conditioning module is connected with the signal processing module, an expert database is established in the memory of the signal processing module, and the display control module is connected with the signal processing module by a serial communication cable. According to the characteristics of acoustic emission signal sources, the detector records the sound characteristics of different stages from sharp to damaged when between different cutting tools and different workpieces, and then establishes an expert database. By storing the expert database in the memory of the signal-processing module, it can identify the cutting tools wear when different machines cut different workpiece, and predict the cutting tools wear.

Sun Yanjie et al. aiming at the shortcomings of single sensor in monitoring cutting tools wear status, put forward the comprehensive utilization of acoustic sensing and force sensing, and used artificial neural network as a multi-sensor information fusion method to monitor cutting tools wear status[13]. The 45# steel tempering workpiece was milled on the vertical NC machining center, and the characteristic quantities related to cutting tools wear were detected by electret microphone and Kistler dynamometer, and the 6th, 7th and 8th order components of linear prediction cepstrum coefficient (LPCC) of milling acoustic signal characteristic quantities were obtained. The cutting forces in x and y directions and the moment around z axis were closely related to cutting tools wear. Taking these six features as the input signals of neural network, a multi-parameter fusion model of cutting tools wear monitoring is established by using BP algorithm with momentum gradient decline. After the training of neural network, the output value of neural network is basically consistent with the actual measured value, and the average error of the sample is 2.25%, and the variance is 3.29%, which indicates that the accuracy and stability of tool wear degree identification are improved after the fusion of cutting sound and cutting force.

Wang Xiaoqiang and others continuously monitor cutting tools wear based on hidden Markov model[14]. Compared with the classification and recognition of discrete cutting tools wear state, users prefer to get continuous cutting tools wear values, thus providing more accurate information for the final control process. In order to monitor the continuous cutting tools wear value, the vibration and acoustic emission signals which are easy to collect are used as monitoring signals, and the time domain features, frequency domain features and time-frequency domain features of the signals are extracted, from which the features sensitive to cutting tools wear are screened out, and the continuous wear value is obtained by hidden Markov model and probability calculation. By comparing the monitoring model using cutting force, acceleration and acoustic emission signals with the monitoring model using only

acceleration and acoustic emission signals, the method that can accurately predict the cutting tools wear value without cutting force signals is found out.

Xu Yanwei et al. [15] set up a multi-information data acquisition system for cutting tools wear state of NC lathe by collecting acoustic emission and vibration acceleration signals, collected relevant data by orthogonal test method, and analyzed acoustic emission and vibration signals in NC cutting process under different cutting conditions and different cutting tools wear degrees. The wavelet packet decomposition method is used to extract the best characteristic frequency band of acoustic emission and vibration signals as the characteristic parameters of cutting tools wear identification. The BP neural network is used to fuse the acoustic emission and vibration signal characteristic information of cutting tools wear in NC cutting process, and the intelligent identification of cutting tools wear state in NC turning is studied.

Liu Chengying et al. established a monitoring system of cutting tools wear state based on acoustic emission. By collecting acoustic emission signals during machining, the amplitude, absolute value mean, root mean square and maximum value of square root were extracted as the time domain characteristic values reflecting tool wear[16]. Aiming at the shortcomings of artificial neural network, such as easy to fall into local minimum, difficult to determine the structure, slow learning convergence, etc., a cutting tools wear state recognition method based on Least Square Support Vector Machine (LS-SVM) is proposed. In view of the fact that the performance of LS-SVM depends on penalty factor and kernel parameters, particle swarm optimization (PSO) algorithm is used to automatically optimize the parameters of LS-SVM, and a PSO-optimized LS-SVM model is established to identify the cutting tools wear state. Compared with the LS-SVM recognition model, the optimized LS-SVM model has higher recognition rate.

Zhang Yanchao et al. selected GH4169 superalloy for milling experiment, and adopted dynamometer and vibration acceleration sensor to collect signals. Low-pass and band-pass filters are used to preprocess the signals, and the sensor signals when cutting tools really participate in cutting are intercepted. The multi-scale principal component analysis model is trained and tested by extracting time-domain and frequency-domain features to form a training sample set and a test sample set. The cutting tools wear monitoring information is displayed by the wear state control chart, and a set of intelligent on-line monitoring software based on virtual instrument technology is developed. The results show that the multi-scale principal component-monitoring model overcomes the shortcomings of the traditional pattern recognition method, has high monitoring accuracy, and is suitable for monitoring the cutting tools wear state of difficult to process materials[17].

Wang Guofeng et al. invented a cutting tools wear state monitoring method based on conditional random field model[18]. Through collecting acoustic emission signals in cutting process, preprocessing and extracting related features value, the extracted feature vectors are used as training samples and test samples of conditional random field model, and the obtained training samples are used to establish conditional random field model for monitoring cutting tools wear state. The test samples are input into the established model, and the corresponding cutting tools wear state is output, so that different cutting tools wear states can be accurately detected, and the cutting tools wear state can be predicted only by analyzing acoustic emission signals generated in cutting process.

Because the milling cuts discontinuously at high speed, the cutting tools wear is rapid and difficult to monitor, which seriously affects the machining accuracy and product quality of the workpiece. Lin Yang et al. put forward a new method for predicting the wear state of high-speed milling tools based on deep learning [19]. In this method, the energy distribution of milling force signals in different frequency bands is extracted by wavelet packet transform as the initial feature vector, unsupervised learning is used to learn the features of sparse self-coding network, and single-layer networks are stacked to form a deep neural network. Supervised learning is used to fine-tune the completely deep network, thus establishing a prediction model of the milling cutting tools wear.

Jiangsu SIGER Data Technology Co., Ltd. has developed SIGER cutting tools monitoring and management system[20], which monitors the state of the cutting tools in the whole cutting process by detecting the current variation of the spindle motor of the machine cutting tools under different cutting resistances. They adopts various optional measures such as sending stop signals, sending cutting tools broken information, warning with three-color lights, etc., and carries out preventive intervention and control in the production process, thus realizing real-time monitoring and analysis of the phenomena such as cutting tools breakage, wear and edge collapse.

Shanghai Zhanwan Information Technology Co., Ltd. has designed a targeted scene application algorithm for the general scenes, robot automatic welding, machining and other fields, which often

encounter difficulties in statistics of output and production tempo, problems such as partial welding, air holes and insufficient penetration during welding, and the cases such as cutting tools chipping, cutting tools breakage and wear during machining. The algorithm function module can quickly configure the corresponding scene application algorithm for the problem, send it to the edge-computing gateway, and realize the real-time monitoring of the cutting tools wear state by artificial intelligence algorithm in the way of edge computing[21].

Lin Bing invented a cutting tools wear monitoring method based on the composite signal of current and acoustic emission. The method detects the current signal of spindle motor and acoustic emission signal of cutting tools wear state in cutting process, and processes and analyzes it based on the composite signal of current and acoustic emission, thus realizing the real-time monitoring of cutting tools wear state. The method adaptively acquires the cutting tools wear state characteristics in the current signal and acoustic emission signal of the cutting motor, fully excavates the cutting tool-wear state information in the current signal and acoustic emission signal of the acoustic cutting motor. By means of wavelet packet analysis, correlation analysis and principal component analysis, the feature information reflecting the current wear state of the tool is extracted adaptively, and the wear degree of the cutting tools is judged by analyzing the correlation between the feature and the initial wear state[22].

Fu Yulong studies the monitoring system of cutting tools wear condition based on multiple eigenvalues of power signal[23]. By comparing the physical signals appearing in the process of cutting tools wear, the spindle power signal is used to monitor the cutting tools wear condition, and the common cutting tools wear forms in parts processing are analyzed. On this basis, combined with the actual processing situation in the production site, the OPC(OLE for Process Control) server of the machine tool numerical control system is used to collect and monitor the power signal of the machine cutting tools spindle. Secondly, due to the fine division of NC program segments and insufficient data collected by individual NC program segments in the process of building the cutting tools wear monitoring system, the NC program segments are redivided. In order to improve the accuracy of cutting tools wear monitoring, the synchronization error between the threshold and the signal caused by frequency fluctuation is eliminated. Thirdly, according to the analysis of spindle power signal, eliminate no-load power signal and additional load loss power signal, extract machine cutting tools cutting power directly related to tool wear, calculate the characteristic value of machine cutting tools cutting power signal, and reflect different characteristics of the signal through characteristic value, thus improving the accuracy of monitoring process. The dynamic weighted comprehensive evaluation method is used to construct a comprehensive evaluation model of cutting tools wear, and the cutting tools wear state is monitored. Fourthly, develop the cutting tools wear monitoring software. Design parts with various machining features, carry out actual machining, and verify the accuracy of the monitoring system. Through the analysis of spindle power signal and cutting tools wear form, the accuracy of cutting tools wear monitoring is improved. In addition, a cutting tools wear monitoring system is designed, which improves the automation degree and production safety of NC machining process.

To sum up, at present, the mainstream research method at home and abroad is to monitor the sensor signals related to cutting tools wear or breakage to realize cutting tools use state monitoring. The monitoring signals mainly include acoustic emission, acceleration, cutting sound, motor current, cutting force, etc. and the fusion of various monitoring information. Through support vector machine, wavelet transform, neural network, hidden Markov model, multi-scale analysis, deep learning and other methods, the monitoring signal sensor data processing and prediction model are established, and the wear recognition rate can reach more than 90%. However, in order to improve the use efficiency of coated cutting tools, it is necessary to judge the time point when the tool coating is worn out accurately to 0.5 second, so as to achieve compatibility with different tool change control systems of machine, and the existing research results need to be further deepened.

3. Measurement of Milling Process Parameters Based Laser Vibrometer

Laser Doppler vibration measurement method based on optical detector has the advantages of high precision and nondestructive [24]. In recent years, scholars at home and abroad have made some progress in precision measurement of bridge construction, precision machining and satellite antenna in aerospace field based on laser vibrometer.

Swagata Banerjee and others used vibration measurement to assess the vulnerability of bridge

structures[25]. Ben J. Halkon et al. used a laser vibrometer to measure the vibration angle (pitch and yaw) directly from the rotor[26]. Akira Maekawa et al. develop a non-contact measurement method for bending and torsional vibration of pressure piping systems using multiple laser displacement sensors[27]. Yarovoi L.K. et al. proposed a new method to reduce the influence of external conditions on laser Doppler vibration signals in the nanometer range[28].

Compared with the advanced level of foreign countries, the overall level of domestic laser vibration measurement technology is behind. In 2013, SUNNY GROUP CO., LTD and many other units jointly undertook the national major instrument special "R&D and industrialization of cross-scale laser Doppler vibrometer", and achieved expected results[29].

Liu Fan measured and studied the vibration characteristics of CNC machine tools based on laser Doppler vibration measurement technology[30].

Huang Juan et al. studied the error of the laser Doppler optical system in the measurement of the bending and torsional vibration of the rotating shaft, and proposed measures to control the error[31]. Zhang Shaobo et al. studied methods to improve the reliability of laser vibration measurement systems[32]. He Yuanrong et al. conducted a laser 3D measurement model and simulation analysis of a large steel building high-rise structure[33]

Based on the laser Doppler vibrometer, our group conducted a preliminary study on the cutting tools wear of the CNC milling machine. Figure 1 shows the time-domain and frequency-domain curves of the vibration signal at the cutting tools holder of the measured undamaged cutting tools, and Figure 2 shows the vibration signal time domain and frequency domain curves at the cutting tools holder of the measured damaged cutting tools. Comparing Figure 1 and Figure 2, it can be found that the time domain and frequency domain analysis of the laser Doppler vibration measurement signal can reflect the cutting tools wear status to a certain extent.

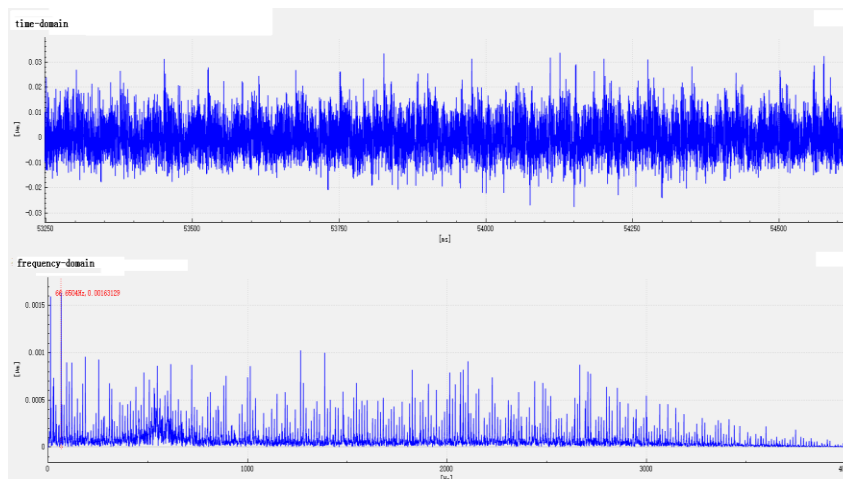


Fig.1: Time-domain and frequency-domain curves of the vibration signal at the tool holder of the measured undamaged cutting tools.

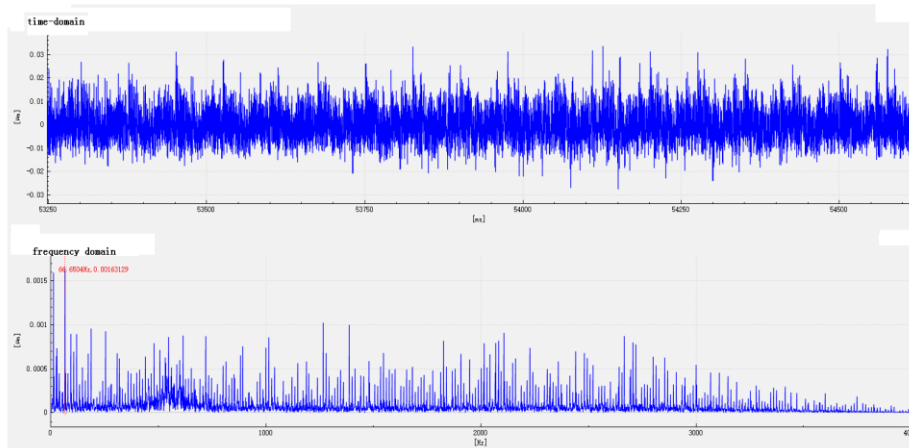


Fig.2: Time-domain and frequency-domain curves of the vibration signal at the tool holder of the measured damaged cutting tools.

4. Conclusions

At present, the mainstream method of monitoring cutting tools wear status of CNC machine at home and abroad is through the monitoring of acoustic emission, acceleration, cutting sound, motor current, cutting force sensor signals and various monitoring information fusion related to cutting tools wear or damage. Through support vector machine, wavelet transform, neural network, hidden Markov model, multi-scale analysis, deep learning and other methods for monitoring sensor data signal processing and establishing prediction models. However, in the CNC milling process of molds, in order to improve the use efficiency of coated cutting tools, it is necessary to judge the time point when the coating of the cutting tools wears out to be accurate to 0.5 seconds, so as to achieve compatibility with different cutting tools change control systems of the machine, and their research results need to be further deepened. Among them, the measurement of the parameters of the milling process based on the laser vibrometer is one of the directions of future research.

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