The fusion analysis between tool failure mechanism and process signal

Sun Jiahuan
School of Reliability and Systems Engineering
Beihang University
Beijing, China
sjh961104@163.com

Dai Wei
School of Reliability and Systems Engineering
Beihang University
Beijing, China
dw@buaa.edu.cn

Wang Bo
AVIC Aerospace System Co., Ltd.
Beijing, China
wang_bo@126.com

Jiang Nan
Beijing Institute of Control Engineering
Beijing, China
nancyjiang_bj@126.com

***Abstract*—The cutting tool condition during machining is closely related to the accuracy and roughness of the workpiece. The realization of the important aspects in intelligent manufacturing, such as perception, analysis and decision-making relies on the condition monitoring technology. As an important concern during processing, a number of studies are being done by many researchers for tool reliability based on condition monitoring technology. This paper will review the fusion analysis between tool failure mechanism and process signal. The methods and objects in this area will be teased out. And an up-to-date comprehensive survey of the cutting process signals, failure mechanism analysis for signal selection and multi-sensor information fusion will be provided. Finally, the future challenges and trends will also be presented.**

Keywords-cutting Tool; fusion analysis ; failure mechanism analysis; signal selection

I. INTRODUCTION

The cutting process is a complex physical process with many types of signals that can be extracted. There are a lot of differences between these signals, such as the acquisition method, sensitivity to the cutting process and processing method. It is important to select the appropriate signal and method to improve the accuracy of the cutting condition monitoring. Therefore, it is crucial to select the signal that is most sensitive to the form of tool failure by the fusion analysis between tool failure mechanism and process signal.

Failure physical analysis is the study of the relationship between the various failure phenomena of the tool (failure mode) and the incentives that cause the failure (stress, including environmental stress and time stress). The fusion analysis between tool failure mechanism and process signal is to study the internal mechanism of the tool in the event of failure, find out the influence of the failure mode on various signals during the cutting process. Thus, the occurrence of tool failure can be monitored and determined by selecting appropriate signals. During the research, the physical signal is converted into an electrical signal by installing a sensor in the processing system. It is transmitted to the computer as a digital signal through an amplifying device and a collecting device, as shown in Figure 1.

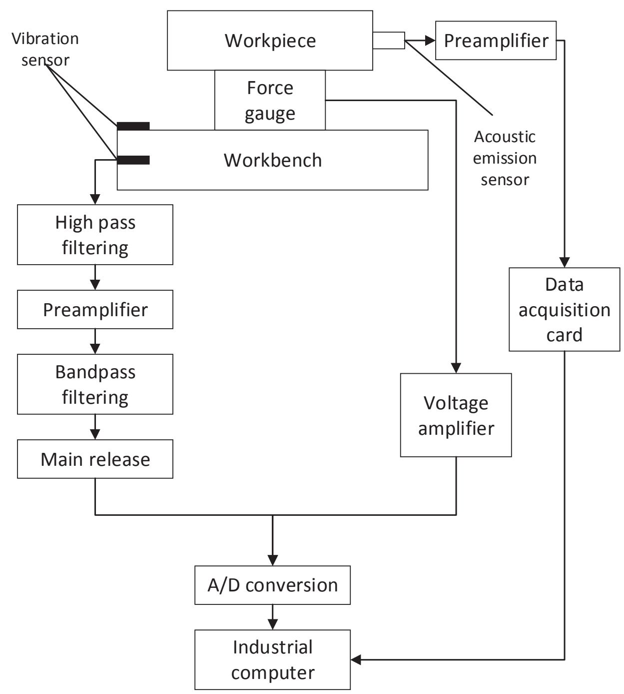

Figure 1. Signal acquisition principle

II. THE CUTTING PROCESS SIGNALS

In terms of tool condition monitoring, the research focuses on cutting force signals, vibration signals, machine power signals, sound signals and acoustic emission signals. These signals were proved to be sensitive to the wear condition of the tool and were used to monitor tool wear in a variety of machining forms such as turning, milling and drilling.

978-1-7281-0860-5/19/$31.00 ©2019 IEEE

A. The cutting force signal

The cutting force signal is generally measured by resistance strain type force gauge and piezoelectric crystal type force gauge. Studies have shown that the change in cutting force is the physical phenomenon most closely related to the tool failure condition. In many studies, the cutting force is decomposed into three directions of X, Y, and Z according to the direction of the spindle feed, which are tangential force, feed force, and radial force. However, the measurement cost of cutting force signal is high. And the measurement also has an influence on the cutting process. By collecting the three-direction cutting force signal and applying the Six Sigma principle and factoring the data, Chen Hongtao et al. [1] proposed an effective method for predicting cutting force in the absence of empirical formulas and testing conditions. This method provides a basis for optimizing cutting conditions. Oraby S E et al. [2] used nonlinear regression analysis techniques to model the effects of various cutting force components on tool wear and tool life.

B. The vibration signal

The vibration signal is generally collected by a piezoelectric acceleration sensor. Vibration is a low-frequency oscillation caused by periodic changes in the cutting component, resulting in changes in the vibration amplitude and vibration frequency of the machining system [3]. Studies have shown that the vibration signal during the cutting process contains a wealth of information on the wear condition and it is easy to monitor. The vibration signal sensor has a simple structure and low cost, so it is also the main signal in the detection of other mechanical devices. The vibration signal is easily affected by the noise of the processing environment, and is often doped with environmental noise. So filtering is often required for research [4]. Julie Z. Zhang et al. [5] studied the relationship between the vibration of the spindle and the feed axis and the tool wear by using the optical system. This method successfully monitored the change in tool wear condition, but the monitoring accuracy was limited.

C. The power and current signal

The power and current signals can be measured directly from the machine motor. When the tool wears, the cutting force will increase, and the load on the machine will increase. It can be reflected in the motor that the power and current increase. Therefore, the measurement of power and current signals avoids the influence of the sensor on the machining process. However, the power and current signals are less sensitive to tool wear. In order to increase the accuracy of monitoring, it is usually necessary to fuse with other signals. RenedeJesus et al. [6] established a model between motor current and tool breakage to predict tool breakage. Wang Junping [7] used stochastic fuzzy neural network to establish the corresponding relationship between tool wear and motor current. This model can identify the tool wear condition in a certain precision range.

D. The Acoustic Emission (AE) signal

The Acoustic Emission (AE) phenomenon was discovered by German scientist Kaiser in 1955. At present, AE technology has been rapidly developed in engineering applications and is recognized as a new monitoring technology with great potential. The Acoustic emission signals can be detected by piezoelectric sensors, which are high-frequency oscillations generated by the release of strain energy in the form of elastic stress waves when the material is damaged [8]. In the machining process, many acoustic emission signals are generated, which are from the tool wear, the deformation of the workpiece, and the friction of the chip. The information of the tool wear is included in the acoustic emission signal, as shown in Figure 2 [9]. Compared with other monitoring methods, the acoustic emission signal has high sensitivity. The signal frequency (100kHz~1Mhz) is higher than the noise frequency, so it can avoid the low frequency band with serious noise during processing. However, the cost of the sensor is high. And a high-frequency signal acquisition device is also required [10].

At present, tool wear monitoring technology based on acoustic emission technology has been vigorously promoted, with the advancement of signal processing technology and the rapid development of computer technology. AE technology is recognized as a promising new monitoring technology. Lots of researchers have proposed monitoring programs under various processing scenarios. Liu T et al. [11] used AE to perform tool wear detection during the cutting process. It is considered that the power spectrum of the AE signal increases with the wear of the tool within 350 kHz, and the sum of the AE counts is closely related to the tool wear. The results of Xiaozhi Chen and others shown that under normal wear and tear, AE mainly comes from the first, second and third deformation zones and is a typical continuous signal. But when the tool is damaged, the AE signal is a discontinuous signal [12].

The following studies use the AE signal for wear monitoring of drills, turning tools and milling cutters respectively. The AE signal can be used to meet the requirements of tool condition monitoring in many aspects. Xie Jianfeng et al. [14] studied the milling process of 45 steel, applied wavelet transform to multi-resolution decomposition of acoustic emission signals, extracted the signal energy of each frequency band as the feature quantity. GómezM P et al. [15] studied a drilling process with different degrees of wear in the drill bit to find relationships between acoustic emission (AE) and torque measured during the drilling process, and also with the degree of wear of the tool. KJemielniak et al. [16] studied the roughing process of Inconel, and used wavelet packet transform to extract the characteristic values such as skewness, kurtosis and energy of the AE signal and the wavelet component coefficient of the cutting force signal. The correlation coefficient method is used to optimize the kurtosis

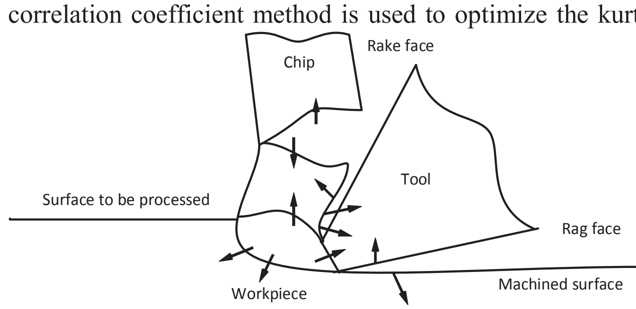

Figure 2. Sources of AE in machining

and energy, and then used Neural network algorithm establishes tool wear model based on cutting force and acoustic emission signal. Zhang Dongliang et al. [17] studied the milling process of aluminum alloy 6061, analyzed the acoustic emission signal by chaotic time series analysis method, extracted the embedding dimension and Lyapunov coefficient of the signal as feature quantities, and established a tool wear monitoring model based on vector machine. Neslušan et al. [19] studied the turning of 100Cr6-62 materials, and used two kinds of AE sensors to separately acquire high-frequency and low-frequency AE signals, and used the relationship between the two signals as the feature quantity to determine tool wear. Nie Peng et al. [20]studied the turning process of GH4169, and used statistical methods and wavelet analysis to extract the root mean square of AE signal amplitude and the energy of [10-150]KHz band as the signal feature quantity, and established a tool wear monitoring model based on wavelet neural network. Zhou Yumeng studied the aluminum alloy turning process, extracted the energy of the AE signal [7.8-31.25] KHz band, and established a tool wear monitoring model based on BP neural network [21]. Maia et al. studied the turning process of AISI 4046 steel. The research showed that the average density of the power spectrum of the AE signal which is closely contact with wear and tear, is high at the initial value of the tool life. As the tool enters the mid-life value, the level of the end of the life is gradually increased [22].

III. FAILURE MECHANISM ANALYSIS FOR SIGNAL SELECTION

For the common defects in the cutting process, the relationship between the failure mechanism and the process signal is summarized. Based on the summary results, the process signal that is most sensitive to a certain failure mode can be selected.

A. Flutter

Flutter is an unstable self-excited vibration that occurs in almost all machining processes. During the cutting process, if the system is subjected to an instantaneous accidental disturbance, the relative vibration of the tool and the workpiece will occur. The amplitude of the vibration will gradually decay due to the presence of the system damping, but the vibration will leave a ring of vibration on the existing machined surface. When the workpiece is rotated one revolution, the tool will cut on the surface with the vibrating surface. As a result, the cutting thickness will be too large or too small, which will result in dynamic cutting force. If the various conditions during the cutting process further promotes the vibration, it will develop into flutter. Strong vibrations also generate a lot of noise, irritating the operators [24].

Because flutter is a strong vibration phenomenon, researchers use the vibration sensor to extract the characteristic quantity from the vibration signal for the monitoring of cutting flutter. In the literature [25], the vibration signal is used to analyze the milling condition. The results show that the vibration signal is more reliable and highly used in related research. In addition, flutter will cause changes in cutting force and generate a lot of noise. Therefore, in addition to the vibration signal, some scholars also use the cutting force and the sound signal. For example, the literature [26] selects the sound signal as the monitoring signal of the milling flutter, and establishes the milling flutter monitoring model. The sound signal is more convenient to collect than the cutting force signal and it does not affect the actual machining.

B. Breakage

Tool breakage typically includes crack formation, expansion, instability, or impact fracture processes. For the monitoring method of tool breakage, many scholars use cutting force [27], machine motor current [28], power [29], vibration [30] and acoustic emission [31] monitoring signals. Among these sensing signals, Acoustic Emission (AE) signals have received extensive attention due to their high sensitivity, anti-interference and easy installation.

Two characteristics of the AE signal can be used to determine whether a crack is formed, as shown in figure 4. The first is the stepwise change of the AE signal count rate when the tool state is gradually worn to severe wear. The second is the sudden AE signal caused by the fracture of the tool material, which has a strong energy. Its amplitude is generally high.

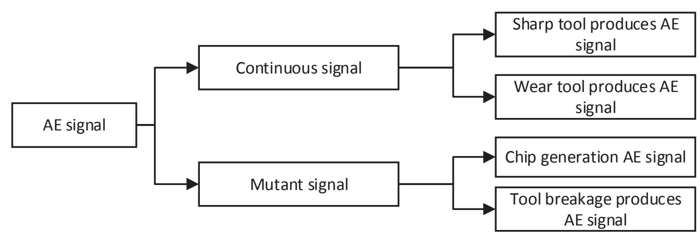

Figure 3. Type of AE signal generated during tool damage

C. Tool wear

Tool wear is one of the most typical phenomena in the machining process. Numerous studies have shown that there are mechanical, thermal and chemical effects in the tool wear process, as well as friction, adhesion and diffusion. It is the result of the combined action of one or more forms of wear. The main cause of tool wear is mechanical heat and chemical wear [32]. Mechanical wear is caused by the scoring of hard spots in the workpiece material. Thermal and chemical wear is caused by the bond and the diffusion.

When the tool is severely worn, the amplitude and the energy of the AE signal generated by the friction between the tool and the workpiece increases due to the increased contact area between the tool flank and the workpiece. And the frequency components will be diversified. At the same time, due to the complexity of the tool wear form, tool wear can also lead to the increase of cutting forces, cutting temperatures and vibration.

Therefore, scholars usually combine a variety of signals, such as cutting force signals, vibration signals, acoustic emission signals, power or current signals to study the wear state of the tool [33].

IV. MULTI-SENSOR INFORMATION FUSION

Due to the external load, the tool will gradually be damaged during operation. The damaged tool will have a certain influence on the output signal during the cutting process. The relationship between external load, output signal, and tool damage is shown in the figure 3. In the figure, $Z(t)$ indicates the external load acting on the tool over time, $U(t)$ indicates the degree of damage of the tool over time, and $X(t)$ indicates the change of the output signal of the cutting process with time [23].

$Z(t)$, $U(t)$ and $X(t)$ are both quantities that change over time. And their relationship can be expressed as:

$$U(t)=\phi(Z(t)) \tag{1}$$

$$X(t)=y(U(t)) \tag{2}$$

It can be seen from the equation that the relationship between the output signal represented by $X(t)$ and the degree of damage represented by $U(t)$ depends on the mapping affected by the tool structure and the failure mechanism. In addition, the physical properties of the tool material itself are closely related to its damage. The damage is the characterization of the microscopic physical process of the tool material. And the process signal is a macroscopic reflection of the tool state change process.

Through the study of the mechanism of tool failure, it can be concluded that the damage of the tool is usually the result of a combination of various factors. It is a complex physical phenomenon caused by high temperature, high pressure and huge intermittent impact. Therefore, tool damage is usually accompanied by a variety of signal changes.

At present, multi-source sensing information fusion technology has been widely used in military and civilian fields, including fault diagnosis, manufacturing process detection and control. Therefore, researchers have also continuously explored the state of tooling in the fusion of multiple signals.

B.BAHR et al. [33] used vibration and visual sensors to detect and identify the wear condition of the tool; Matsushima et al. [34] proposed to combine the various sensor signals or at least the sensor information of multiple sensors to evaluate the tool machining state and tool failure; Chryssolouris G et al. applied multi-source sensing information by neural network, group clustering and least squares regression method, and compare the performance of the monitoring system. The experimental results show that the tool monitoring system with multi-source sensor is applied. The accuracy is improved over a single sensor.

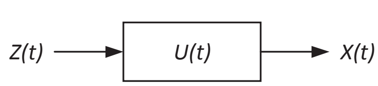

Figure 4. Relationship between external load, output signal, and damage

Liang Jiancheng et al. [35] identified the research object as the milling process, and applied the sensor to separately acquire the signal of three directions of force and acceleration, as well as the acoustic emission signals, extract their feature vectors and use parameter features such as feed rate, Spindle speed and depth of cut, etc., as additional inputs to the neural network, yield satisfactory results for identifying tool wear conditions. Lu et al. [36] use multi-sensor data fusion intelligent system to detect the state of grinding wheel through mechanical signal and acoustic emission signal. Through the proposed multi-signal processing method based on artificial immune algorithm, the monitoring accuracy can be continuously improved; Chen Quntao used sound sensors and vibration sensors as signal detection components to analyze the technical problems related to tool damage monitoring during milling process using multi-sensor information fusion technology. Chen Gang et al. of Beijing Institute of Technology collected cutting during cutting. The force and vibration signals are extracted by time domain analysis, frequency domain analysis and wavelet packet analysis. Then, the feature selection algorithm in the filtering method is used to complete the feature selection. Finally, the input is input to the three-layer BP neural network for training. The results show that the recognition accuracy will be higher after feature fusion, whether it is cutting force signal or vibration signal.

V. CONCLUSION AND OUTLOOK

This paper describes the types of signals generated during the cutting process，as well as the relationship between these signals and the form of tool damage. It is crucial to choose the signal that is most sensitive to the failure form of the tool. This paper combines signal selection methods with the tool failure mechanism analysis.

The damage of the tool is usually the result of a combination of various factors. It is a complex physical phenomenon caused by high temperature, high pressure and huge intermittent impact. Therefore, tool damage is usually accompanied by a variety of signal changes. The application of multi-sensor information fusion is mainly to make accurate judgment and prediction of the state and real-time reliability of the tool through the comprehensive processing and analysis of various signal data.

REFERENCES

[1] Chen H.T,Huang S,Li D.W.Study on the cutting force prediction of CNC turning[J]. Modern Manufacturing Engineering,2010(06):36-39.

[2] Oraby S E, Hayhurst D R. Tool life determination based on the measurement of wear and tool force ratio variation[J]. International Journal of Advanced Manufacturing Technology,2004,44:1261-1269.

[3] Zhang S.M,Mao D,Wang B.Y.Application of big data processing technology in fault diagnosis and early warning of wind turdine cearbox[J]. Automation of Electric Power Systems,2016, 40(14):129-134.

[4] Henriquez P, Alonso J B, Ferrer M A, et al. Review of Automatic Fault Diagnosis Systems Using Audio and Vibration Signals[J]. IEEE Transactions on Systems Man & Cybernetics Systems, 2014, 44(5):642-652.

[5] Julie Z. Zhang, Joseph C. Chen. Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system. The International Journal of Advanced Manufacturing Technology,2008,39(1-2):118-128.

[6] RenedeJesus, Romero-Troneoso Gilberto, Herrera-Ruiz. Driver current analysis for senseless tool breakage monitoring of CNC milling machines[J]. International Journal of Machine Tools and Maunfacture,2003,43(15):1529-1534.

[7] Wang J.P,Jing Z.L,Wang A. Tool wear estimation by soft-sensing technology based on stochastic fuzzy neural network[J]. Information and Control,2002,31(06):534-537.

[8] Guan S. Technology of classification and forecast of tools wear based on muti-feature analysis and fusion of AE[D]. Jilin University, 2011.

[9] Ghosh N, Ravi Y B, Patra A, et al. Estimation of tool wear during CNC milling using neural network-based sensor fusion[J]. Mechanical Systems & Signal Processing, 2007, 21(1):466-479.

[10] Chen P. AE-Based fault diagnosis of milling cutter[D]. Nanchang Hangkong University, 2011.

[11] Liu T, Veidt M. Single mode Lamb waves in composite laminated plates generated by piezoelectric transducers[J]. Composite Structures,2002,58:381.

[12] Xiaozhi Chen, Beizhi Li. Acoustic emission method for tool condition monitoring based on wavelet analysis[J]. The International Journal of Advanced Manufacturing Technology,2007,33(9-10):968-976.

[13] TANSEL I, TRUJILLO M, NEDBOUYAN A, et al. Micro-end-milling—III. Wear estimation and tool breakage detection using acoustic emission signals. Int J Mach Tools Manuf [J].International Journal of Machine Tools & Manufacture, 1998,38(12):1449-1466.

[14] Xie J.F,Wang H.L. Tool Breakage Feature Extraction and Optimization in Milling Using Acoustic Emission[J]. Modular Machine Tool & Automatic Manufacturing Technique, 2011(05):14-17.

[15] GÓMEZ M P, HEY A M, RUZZANTE J E, et al. Tool wear evaluation in drilling by acoustic emission[J]. Physics Procedia, 2010,3(1):819-825.

[16] JEMIELNIAK K, KOSSAKOWSKA J, URBAŃSKI T. Application of wavelet transform of acoustic emission and cutting force signals for tool condition monitoring in rough turning of Inconel 625[J]. Proceedings of the Institution of Mechanical Engineers.part B.journal of Engineering Manufacture, 2011,1(-1):1-7.

[17] Zhang D.L,Mo F,Sun H.B. Tool wear state recognition based on chaotic time series analysis and support vector machine [J]. computer integrated manufacturing systems, 2015(08):2138-2146.

[18] Hu J.L,Zhang S.W,Li L. Research on Tool Wear Monitoring by Acoustic Emission Technology [J]. Tool Engineering, 2012(03):67-69.

[19] NESLUŠAN M, MIČIETA B, MIČIETOVÁ A, et al. Detection of tool breakage during hard turning through acoustic emission at low removal rates[J]. Measurement, 2015,70:1-13.

[20] Nie P,Xu T. State recognition of tool wear based on wavelet neural network [J]. Journal of Beijing University of Aeronautics and Astronautics, 2011(01):106-109.

[21] Zhou Y.M.Tool wear monitoring based on acoustic emission technology[D]. Henan University of Science and Technology, 2014.

[22] MAIA L H A, ABRAO A M, VASCONCELOS W L, et al. A new approach for detection of wear mechanisms and determination of tool life in turning using acoustic emission[J]. Tribology International, 2015,92:519-532.

[23] Yang P. Research on online condition monitoring based prognostics of key parts and components of mechnicanic equipment[D]. University of Electronic Science and Technology of China ,2016.

[24] Gu T.R,Xiao F.Z,Guo W.Cutting flutter mechanism and control [J]. Metal Working(Metal Cutting), 2010, 26(10):36-38.

[25] Tangjitcharoen S. Development of Chatter Detection in Milling Process[J]. Internation Journal of Advanced Manufacture Technology, 2013, 65(23):919-927.

[26] Altintas Y, Chan P K. In-process Detection and Suppression of Chatter in Milling[J]. International Journal of Machine Tool and Manufacture, 1992, 32(2):329-347.

[27] Shao H, Wang H.L, Zhao X.M. A cutting power model for tool wear mentoring in milling [J]. International Journal of Machine Tools & Manufacture.2004, 44:1503-1509.

[28] Prickett P.W, Johns C. An overview of approaches to end milling tool monitoring [J]. International Journal of Machine Tools & Manufacture.1999, 39:105-122.

[29] Marinescu I, Axinte D. A time-frequency acoustic emission-based monitoring technique to identify workpiece surface malfunctions in milling with multiple teeth cutting simultaneously [J]. International Journal of Machine Tools & Manufacture.2009, 49:53-65.

[30] Holmberg K, Matthews A. Coatings tribology-properties, techniques and applications insSurface engineering[C]. Tribology Series,1994(28),Part Ⅱ,United Kingdown:354-358.

[31] Chen H.T. Study on tool wear monitoring and prediction technology based on multi-parameter information fusion[D].Southwest Jiaotong University, 2013.

[32] Niu Z.Y. Research on Multi-sensor Information Fusion Technology in Modern Warfare [J]. Computer and information technology, 2006(3):71-73.

[33] Yang Z.Y,Han Q.S.Sun Z.Y.A review about multi-sensor information fusion and its application in machining process[J].Modern Manufacturing Engineering, 2007(10).

[34] Bertok P, Takata S, Matsushima K, et al. A system for monitoring the machining operation by referring to a predicted cutting torque pattern [J]. CIRP Annals - Manufacturing Technology, 1983, 32(1): 439-444.

[35] Liang J.C,Li S.Y,Wen X.S.Research on Quantitative Monitoring of Tool Wear Based on Neural Network and Multi-sensor Fusion [J]. Mechanical Science and Technology for Aerospace Engineering, 1995, (6): 125-130.

[36] Lu Z J, Xiang Q, Xu L. An application case study on multi-sensor data fusion system for intelligent process monitoring [J]. Procedia Cirp, 2014, 17: 721-725.