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Machining process monitoring and application: a review

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Abstract: Machining data have been increasingly crucial with the development of modern manufacturing strategies, and the explosive growth of data amount revolutionizes how to collect and analyze data. In machining process, anomalies such as machining chatter and tool wear occur frequently, which strongly affect the process by reducing accuracy and quality as well as increasing the time and cost. As a typical type of machining data, signals acquired in real time by advanced sensor techniques are widely embraced to detect those anomalies. This paper reviews the recent development and applications of process monitoring technologies in machining processes, and typical application scenarios in machining processes are discussed with the latest literatures and current research issues. Potential future trends of process data monitoring and analysis for intelligent machining are put forward at the end of the paper.

Keywords: Machining; monitoring; machining data; prediction

1. Introduction

Machining data is becoming critical and vital nowadays. According to the research of Yin and Kaynak[1], data generated by manufacturing systems is growing explosively in modern manufacturing industry, which has topped 1000EB from statics in 2015 and is expected to increase 20-fold in the next ten years. In the context of industry 4.0, manufacturing systems are updated to be intelligent.[2] The analysis of machining data will bring more informed decisions, which improves the effectiveness of intelligent manufacturing. Therefore, data-driven manufacturing is considered as a necessary condition for intelligent manufacturing, and data is becoming a key part to enhance manufacturing competitivesness.[3]

Machining data can be collected in various ways. Typically, as a main data type of machining data, monitoring signal plays a vital role in data-driven manufacturing. Sensors technologies are increasing adopted to obtain data at all stages of the life circle of a product, and there is no exception for machining process, which determines the final quality of the product. The monitoring of machining processes is economical and practical owing to it helping to detect tool wear, machining chatter, and other anomalies that causing waste, damage or even rejects during machining.[4] So far, there exists substantial research contributions in the area of data-driven machining,[5] and data monitoring and analysis is still a hotspot as more and more researchers start to realize the importance of machining data. This paper discusses the applications of monitoring and data analysis in machining processes, with the purpose of concluding the state-of-art briefly and forecasting the potential development and trends in this area.

The rest of this paper is organized as follows. Section 2 makes a brief introduction of the monitoring signals in machining, followed by typical applications of monitoring and analysis techniques presented in Section 3. Finally, Section 4 draws the conclusion and gives research issues for future research.

2. Machining Process Monitoring Methods

Monitoring techniques have been embraced in machining processes due to their helping to identify tool wear, machining chatter, and other anomalies during machining. The widespread deployment of various types of sensors enable the machining systems to achieve real-time monitoring. Common monitoring signals include cutting force, vibration, current, sound, and acoustic emission. The machining monitoring system is shown schematically in Fig. 1.

Due to the high correlation with the real-time status of tool and workpiece during machining, the monitoring technique of cutting force is the first to be achieved and still investigated and developed in recent studies. Cutting force signals can be captured by dynamometer directly.[6] However, the high cost and limitation to the size of the workpiece hamper the use of the dynamometer in real production. To avoid the drawbacks of dynamometry, researchers

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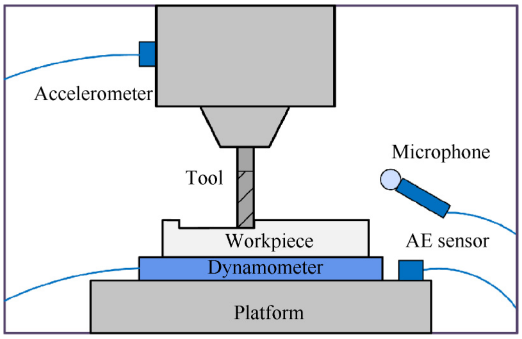

Fig. 1. Machining monitoring system with multiple sensors

adopt embedded sensors, such as sensor integrated fixture or insert cutter to measure process forces. For example, Liu et al.[7] designed a sensor integrated fixture system for aircraft structural parts. Based on the force measuring model, the designed system was validated and has a high agreement with standard dynamometer. Luo et al.[8] presented an instrumented wireless milling cutter system with embedded thin-film sensors, and the cutting force signal can be captured without effects on stiffness and dynamic characteristics of the machining system.

Machining vibration monitoring is also a hot research topic in metal cutting process, since it is the primary reason that causing unstable machining and even rejects, mainly because of chatter, and features are extracted from vibration signals to identify machining state. Vibration signals can be obtained by several distinct sensors, and accelerometer is a prevalent choice for vibration monitoring for its high sensitivity and flexibility.[9] Accelerometer was mounted on the workpiece, and the monitored vibration signals were processed by mode decomposition to detect machining chatter.[10] For machining state monitoring, Fu et al.[11] proposed an automatic feature construction method to establish the relationship between vibration signal and machining state. Besides, machining vibration can be monitored by PVDF sensors integrated in the fixture, hence without interference to the material removal process.[12] This embedded monitoring method enables the in-detail close monitoring and study of the machining process.

Research on sound signal monitoring may be inspired by the experience of machine operators, who judges if the machine works in a stable status by listening the sound. Based on this intuition, sound signals acquired by microphones are for diverse purposes in different machining processes. Dang et al.[13] analyzed the chatter in milling of pocket-shaped workpiece by sound signal monitoring, and this audible signal was also employed in turning[14] and grinding[15] process. Moreover, the acoustic emission (AE) is another kind of acoustic wave signal that occurs due to the rapid release of energy within a material under plastic deformation. In traditional machining, AE signal is generated after the cutting tool removes material from the workpiece during machining, thus engaged in process monitoring. Based on this, Seid et al.[16] applied AE signals to monitor the built-up edge during machining, and the tool wear can be evaluated by processing AE signals[17]. AE signal can be also implemented in additive machining process to diagnose the process failure.[18]

Additionally, the current signal generated from feed current system is an important condition evaluation index for machine tools, which can be used to analyze the machining dynamics[19] and drive system dynamics, working condition as well as life cycle assessment[20]. For advanced machine tools, real-time current signal can be gained without additional instruments, and it often converted into other physical quantities to realize process monitoring. Aslan et al. proposed a model to identify cutting forces from the feed drive current measurements in five-axis milling process, which can be performed for both condition monitoring and as well as adaptive control of maximum forces.[21] With signals from the machine tool itself, no sensor installation is required, and the cost is low while the prediction capacity can also be ensured for some cases.

Extensive research about process monitoring has been carried out for various machining processes, and multifarious sensors and signals are involved for different purposes. Nevertheless, many existing monitoring techniques have limited feasibility in practical application, mainly because of their low flexibility and high interference to the machining process. Consequently, future research on sensor-integrated and embedded-sensing techniques will be potential hotspots in real-time machining monitoring area, such as intelligent spindle or fixture system, which will be core components of the next generation of smart equipment and help to realize self-sensing.

3. Machining process prediction based on monitoring data

Machining process is critical and vital to the life cycle of the product. As discussed above, various signals can be obtained by monitoring techniques implemented on machine systems. Raw signals captured by sensors contain stochastic noise and convey limited visible information to help the decision of technicians and machine operators. Therefore, processing procedures are supposed to be conducted on raw signals to extract useful features for further analysis. The captured data are converted into knowledge and decisions to achieve the purposes of real-time monitoring, mainly referring to those research highlights, such as condition monitoring during machining processes.

3.1 Part condition prediction based on monitoring data

The primary goal of the machining is to produce qualified products, and further realize the high-quality and high-efficiency processing. To this end, the condition of in-process part or workpiece is supposed to be monitored during machining process. Surface finish and dimensional accuracy are two main criteria that directly reflect the final quality of products. In general, the inspection operations of these tow criteria are subsequently to the machining process. These post-processing based operations can get accurate results by using precision instruments, but they have no capability to take response actions in time to avoid further quality loss during machining. Thanks to the development of sensor and data analysis technologies, part condition prediction based on real-time monitoring data provides a new way to detect the machining quality in real time.

Surface finish is indicative of both workpiece and process quality in CNC machining, and surface roughness is one typical assessment parameter for it. To monitor this parameter, the idea of mainstream approaches is to collect process signals and establish the relationship between surface roughness and monitoring signals, such as the usage of cutting force signals[22-23] and acoustic emission signals[24]. Nevertheless, the nature of uncertainty in experiment and machining process limits the monitoring and prediction accuracy of these methods. More importantly, these mainstream approaches treat the surface quality as one single value, which is not capable for real-time and local surface monitoring. Researches that treats the surface roughness as time-series data and establish the relationship between the roughness as well as the time-series monitoring signals are urgently required.

Another vital indicator on the workpiece of machining quality is the part deflection or deformation. Parts that contains thin-walled structures are very sensitive to the dimensional accuracy, since the deflection occurs on thin-walled components constantly. In the machining process, it is mainly caused by two reasons, one is elastic deformation by large cutting force, and the other is plastic deformation by residual stress.[4] In CNC machining, the deformation of workpiece can be measured by on-machine probe with a high measurement accuracy and compensated by the proposed geometric modeling[25], but it will interrupt the machining process or be conducted between or after machining steps to measure the dimensional error, which increases the time cost and may not be capable for on-line deformation monitoring. To realize real-time prediction and diagnosis, novel strategies are put forward for different issues. With respect to the deflection caused by cutting force, Luo et al. presented a rea-time nonintrusive method for deflection monitoring and discussed the workpiece deflection for different stages of the whole machining process.[26] By monitoring and analyzing the output voltage captured by PVDF sensors, the deflection can be quantified after calibration, and meanwhile the vibration during machining can be monitored. With regard to the deformation caused by residual stress, common solutions are analytical model and FEM simulation to analyze and predict it.[5,27] However, both common methods have to make a lot of simplifications, which causes a unavoidable accuracy loss of deformation monitoring. Based on previous works of residual stress, Zhang et al. proposed a novel in-processes active control method for residual stress and predict the machining distortion caused by residual stress.[27-28] The proposed method aims to balance the internal stress and prevent the redistribution of residual stress after machining, which analyzes the machining-induced residual stress with the help of clamping force and displacement sensors. The novel prediction and control strategy were verified on the specimen and freeform surface part, and the results showed its feasibility and effectiveness.

With the development of sensor and data analysis technologies, real-time and on-machine part condition prediction and diagnosis strategies have turned up and made efforts to substitute for traditional empirical models and FEM simulations. It is worth noting that the real-time monitoring method for part condition prediction still exists space for improvement such as the accuracy and computation efficiency, and the prediction should not only aims at the entire part, but also focus on the local defects on the part.

3.2 Machining chatter detection and analysis

Machining chatter, especially the regenerative chatter, can decrease the productivity, tool life and surface quality significantly and even cause rejects. According to the reviews of machining chatter[29-31], mechanism-based chatter research focuses on online chatter detection, offline chatter prediction and chatter suppression and control, as exhibited in Fig. 2.

Chatter prediction and online chatter detection are the premises of chatter suppression and control, and two premises are both based on chatter mechanism and can be verified mutually.

Online chatter detection is an essential research topic, not only because it is the basis of chatter suppression and control, it is also more likely to be applied in real production compared with offline chatter prediction with stability lobe. Based on signal processing approaches, valuable latency information of signal can be mined and analyzed to detect chatter. For time domain analysis, Liu et al.[32] identified the milling chatter with the combination of the dynamics of thin-walled workpiece, and signals are analyzed with machined surface in time domain. Nevertheless, knowledge contained time domain is finite, and time domain analysis results can be easily misled by the noise. The chatter mechanism reveals that chatter causes frequency redistribution. Therefore, some scholars adopted frequency domain and time-frequency analysis to detect chatter. For example, Aslan and Altintas[33] presents an online chatter detection method by monitoring current signal and analyzing it in frequency domain. Caliskan et al.[34] utilized a KALMAN filter to sepa-

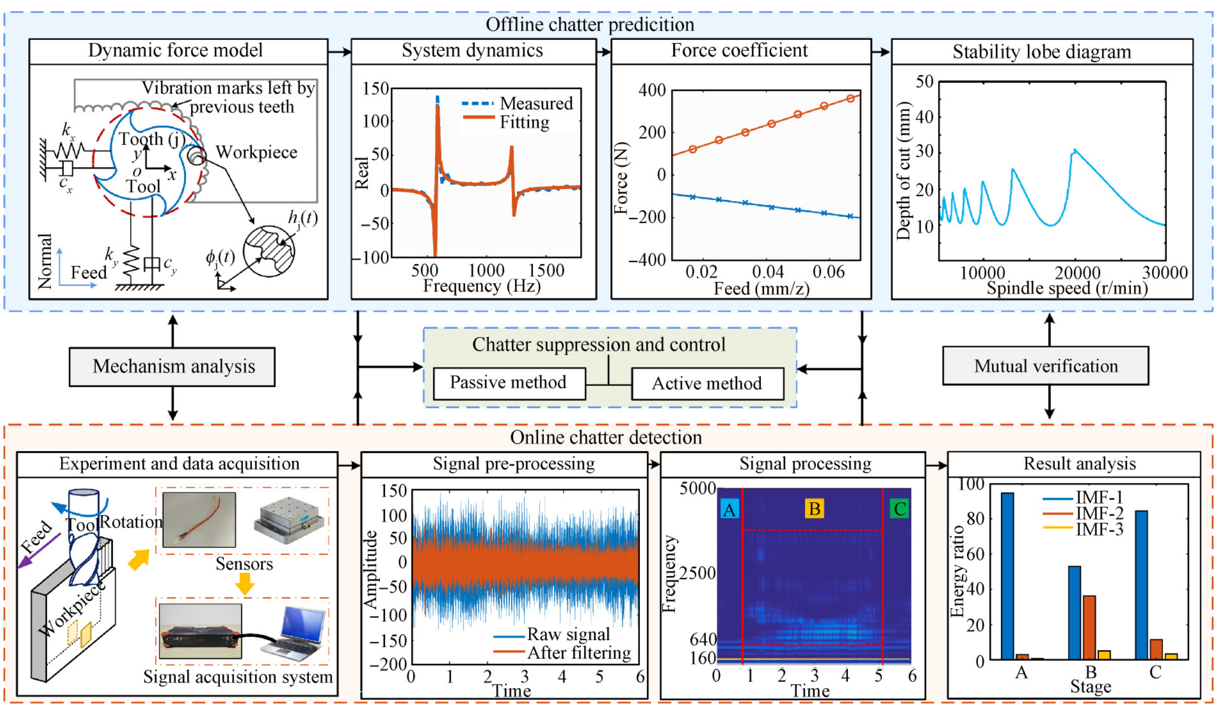

Fig. 2. Three topics of chatter research and their relationship

rate the spindle rotation and chatter components from raw signals on account of chatter mechanism, and chatter was identified relying on fast Fourier Transforms. Furthermore, time-frequency analysis was widely performed in chatter detection as the occurrence of chatter is transient, such as wavelet transform(WT)[12], wavelet packet transform(WPT)[35] and Hilbert-Huang transform (HHT)[36]. Among those time-frequency analysis methods, chatter detection on account of mode decomposition and entropy becomes more and more popular in recent years. Within this method, signals were decomposed and reconstruction by mode decomposition method, and the reconstructed signals were analyzed based on energy entropy.[37-38] Besides, Yang et al.[39] proposed an optimized variational mode decomposition method to identify chatter in advance, and results demonstrated that the proposed method had greater sensitivity and stability than existed decomposition method. Li et al.[40] first subtracted the periodic component of signals, and multi-scale entropy of residual part related to chatter was calculated. Based on the selected features, the gradient tree boosting was conducted to diagnose the severity level of chatter.

Machining chatter has been mature in research, but there still exists problems and limitations to be solved[21] before realizing industrial applications: (1) The signal type, and one or multiple signals are supposed to engaged are still worth investigating in the future. (2) Feature selection and extraction are difficult in industrial application because they need professional knowledge and experience. (3) Signal analysis also requires expertise, and what workshop staff need is a manufacturing system that containing the function of chatter detection. Hence, future works may focus on those limitations and achieving the chatter detection, prediction, and control by intelligent machining systems.

3.3 Tool condition monitoring and analysis

Research on tool condition has been a focus both in academic and industrial area, owing to its direct influence on productivity, cost, and machined surface integrity, where worn tool will significantly decrease these machining indexes. Traditionally, time periods of tool replacement were uniform and determined by the subjective experience of operators.[41] Such strategies inevitably lead to two undesired conditions. One is the early replacement of workable tool, resulting in the increase of cost and machining downtime. Another is the late replacement of worn tool, thus lowering the machining quality and raising the processing costs. As a result, tool condition monitoring system have been developed in order to detect tool wear, maintain machining accuracy, and prevent tool from beakage.[42] The frame work of tool monitoring system is displayed in Fig. 3.

Tool condition monitoring methods can be classified into direct methods and indirect methods. Direct methods such as optical scanning can measure the tool wear with more precise results compared with indirect ones. However, operations must be interrupted to carry out the measurement, which strongly affects the machining efficiency and quality. This drawback limits the application of direct measurement, so indirect methods with various monitoring signals is developed. Generally, signals captured from tool condition monitoring system are filled with noise because of the messy and complicated environment of industrial machining. In addition, algorithms are more apt to fall into the over-fitting and poor generalization when handling the raw data directly in cases of new samples.[43] Consequently, suitable signal pre-processing and processing are required to denoise and extract knowledge and decision from monitoring data, respectively. With the help of domain knowledge and

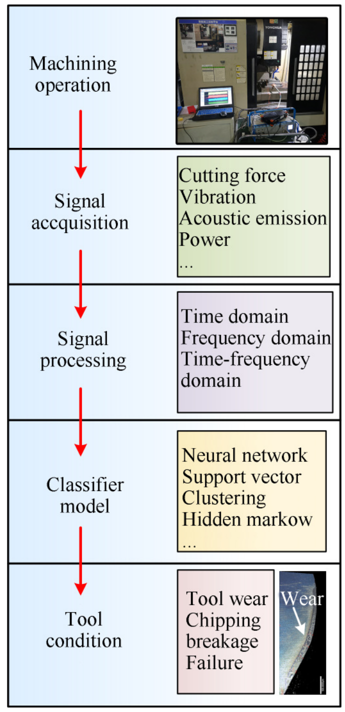

Fig. 3. Frame work of tool monitoring system

advanced algorithms, extracted signal features that are sensitive to tool conditions are utilized to train the tool wear model.

Similar with machining condition monitoring and analysis, features for tool wear detection are generally from the time, frequency, and time-frequency domain. For the time domain, features such as mean, variance, skew and kurtosis are chosen for tool wear monitoring.[44] In frequency domain, Fourier transform is a common method for signal processing to obtain features such as power spectrum as well as tooth passing frequency.[45] However, both time domain and frequency assume that the signal is static, and they only express information from a single perspective, thus not suitable for non-static signals.[46-47] Therefore, time-frequency domain features are employed to reflect the tool conditions. Wavelet transform[48] and its derivations[49-51] are widely used to process signals for feature extraction. Moreover, researchers also make progress in tool condition monitoring by applying multi-domain features.[52-53] To further realize the tool condition identification, the classifier model is established by different approaches based on extracted features. According to the statistics of cited reviews[41,47], artificial neural network and its derivations are the most popular in tool wear modeling. And as the amount of machining data increase and reaches the level of big data, deep learning methods[54] will gradually replace the classic artificial intelligence analysis, as introduced in detail in the review.[43] Other classifier models, like hidden Markov model[53] and support vector machine[55], are also available in tool condition monitoring.

Tool condition monitoring is extremely complicated owing to the influence of various uncertain factors, such as workpiece material, processing types, and environment conditions involved in machining process. The development of related research and techniques are interfered by these challenges and, and thus there exists critical issues need to be further studied: (1) Uncertainties in monitoring signal are needed to be described and quantified, which significantly influences the identification and prediction results of tool condition. (2) The sensor and feature configurations can be further optimized. Multiple high-performance sensors can obtain more accurate results but require high cost at the same time, so it is necessary to find a balance between the cost and the monitoring accuracy. (3) Published methods are generally conducted under fixed cutting conditions, they are difficult to be used in industry where the cutting conditions change quickly. Current proposed models usually have a high accuracy in typical research application, but they may have poor adaptability if applying in a new scenario. Hence, future works may focus on those issues, to ensure that the tool condition monitoring system can remain practical in actual machining environment.

4. Conclusion and future trends

Data has been playing a vital role in manufacturing process, and data collection and analysis have been developed to adapt to increasing demands in modern manufacturing. Machining process monitoring is an important aspect for the operations, maintenance, and optimal scheduling of advanced manufacturing systems. This paper has reviewed contributions to monitoring and analysis techniques applied in machining process. Three typical applications, part condition prediction, machining chatter detection and tool condition monitoring are discussed with research and application issues. Valuable information mined from monitoring data makes it possible to understand the process condition in real time.

Thanks to the advanced sensor technologies and remarkable achievements of machining data analysis, manufacturers have realized the importance of machining data and started to collect the data. However, most manufacturers have no idea what to do with the data they have, let alone how to analyze them to improve the machining processes. What they really need are software and intelligent systems to analyze data and make decisions directly and automatically. To solve the above issues, future work can focus on following possible and potential research points:

(1) Develop of real-time data processing and automatic decision-making methods.

High detection accuracy but time consuming methods are not suitable in practical applications. Therefore, it is important to propose and develop real-time data processing approaches to adapt to the time-variant environments. In addition, algorithms and models applied in monitoring systems are supposed to be automatic to carry out the feature extraction, result analysis, and decision making in order to achieve real-time requirements in actual processing.

(2) Integrate the monitoring and analysis technologies into intelligent equipment to enable self-sensing.

The existed achievements of data monitoring and analysis have good performance in experiment but limited feasibility in practice if applied them directly. To face this challenge, progress has been made on advanced sensor-integrated equipment without interference to machining process, such as intelligent spindle[56-57], tool holder[58] and fixture system[59-61], which are both critical parts for advanced machine tools. Although more achievements and researches focus on mechanics and data processing technologies, intelligent equipment will have more appealing to manufactures due to its more possibility to actual applications.

(3) Data driven machining process system optimization.

Data-driven manufacturing has received great concern and the framework and applications of it are developed in recent years. The monitored machining process big data has been demonstrated its potential ability in machining process intelligent optimization. The concept of digital twin has gained significant impetus as a breakthrough to promote the evolution of manufacturing.[62] This monitoring-data-based technology will be a fruitful area in research and practice in the future.

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