Journal of
Advanced Manufacturing Science and Technology
jamst@jamstjournal.com；jamst2020@126.com
www.jamstjournal.com

Application of audible sound signals in tool wear monitoring: a review

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Received 7 May 2024; revised 20 May 2024; accepted 17 June 2024; Available online 27 June 2024

Abstract: Tool wear condition monitoring (TWCM) has been a research hotspot for decades because of its significance for intelligent manufacturing. However, it has been little applicated in practice despites of its large number of publications. One of the crucial reasons is that the employed monitoring sensors, such as force, vibration, temperature and acoustic emission would disturb the nature processing conditions, which limited their applications in practice. The microphone sensor, which collect audible sound (AS) signal, is considered to be a prospective strategy for TWCM, because it has the advantages of closely related to tool wear, no need to attach sensors, convenient installation, flexible measurement, and no effect on the nature processing conditions. However, tool wear condition monitoring based on audible sound signal (TWCM-AS) is hindered by its insufficient accuracy. Therefore, this study serves as a resource for researchers and manufacturers by providing the recent trends in TWCM-AS. The generation mechanism of cutting AS through physical properties and practical experiments were concluded. Four key technologies, including acquisition, denoising, feature extraction and decision-making algorithm were discussed in detail. And future researches were point out, such as datasets, initiative denoising system, feature extraction of AS and interpretable decision-making algorithm.

Keywords: Tool wear condition monitoring; Audible sound; Denoising; Feature extraction; Machine learning

1. Introduction

Machining processes, such as milling, turning and drilling have been widely used in aviation, aerospace, medical, electronics, mold and other manufacturing industries. These processes are usually accompanied with high temperature, high pressure and strong friction, which result in rapid tool wear and reduce the reliability of the processing system. In general, tool failure contributes about 7% to the down time of machine centers [1]. And more severely, tool failure will reduce the machining quality of parts, and even damage the machine. Thus, tool wear condition monitoring (TWCM) is an important part of intelligent manufacturing, and has been a research hotspot since 1968 [2].

TWCM can be divided into two methods according to the sensor types: direct method and indirect method. The direct method uses vision or laser sensors. Although it has high precision and reliability, it is difficult to achieve online real-time monitoring because these sensors are easy to be affected by cutting fluid, chips and other processing environment interference. The indirect method uses force, vibration, current, acoustic emission, or microphone sensors, which has the advantage of online real-time monitoring.

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Peer review under responsibility of Editorial Committee of JAMST
DOI: 10.51393/j.jamst.2025003
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The force sensor is credited with the best accuracy, sensitivity, and stiffness. However, it is unfeasible for manufacturers because it restricts the maximum workpiece size. The main advantage of vibration sensor and acoustic emission sensor is its linearity over a broad frequency range. But they should be attached physically, magnetically, or adhesively to a mechanical device, and will be greatly affected by the installation location. The installation of current sensors is convenient since the sensor can be placed outside the machine. But current sensor predicts tool failure and severity later than other sensors, because of the “Hall Effect” principle. Compared with force, vibration, current and acoustic emission sensors, the AS signal collected by the microphone has the advantages of closely related to tool wear, no need to attach sensors, convenient and flexible measurement, and does not affect the normal operation of the equipment. Thus, it is considered to be the most suitable for online real-time monitoring of tool wear [3-7]. The comparison of TWCM methods is listed in Table 1.

Machining process condition monitoring (MPCM) aimed to online detect tool wear, cutting chatter or other abnormal conditions, and it had the similar theories and methods to TWCM. Therefore, in order to present a more comprehensive overview, some publications belonging to MPCM but not TWCM were also cited, such as publications about chatter monitoring was cited in the study [4].

In the TWCM field, more than 25 review papers had been published since 1995 [8], including comprehensive introduction [9-22], emphasis on the sensors [23-26], emphasis on signal processing [5, 27, 28], emphasis on the decision-making algorithm [29-35]. However, the review about TWCM-AS had not been reported. At present, we have found a review of AS-based fault diagnosis [3, 36]. But, the main object of this review is rotary bearings, which was quite different from the more complicated cutting process. So, a review about TWCM-AS is needed.

The structure of the review was as follows: (1) literature research and analysis about the publications in the past 10 years, (2) physical definition and characterization of machining AS, (3) generation mechanism of milling AS, (4) research progress of some key technologies, including acquisition, denoising, feature extraction and decision-making algorithm, and (5) research prospects.

2. Literature research and analysis

Publications about AS-based monitoring in the Web of Science database (from 2014 to 2023) were presented in Fig. 1. The keywords “audible sound” was synonymous with sound, audio, acoustic and noise. In order to distinguish it from acoustic emission signals, the keywords "emission" was excluded in the search equations. Therefore, four retrieved results were obtained.

Fig.1(a) was the TWCM-AS, and the search equation was Index_1: TS=("tool") AND ("wear" or "condition" or " monitoring " or "life") AND ("sound" OR "audio" OR "acoustic" OR "audible" OR "noise") NOT("emission").

Fig. 1(b) was about TWCM without sensor limitations, and the

Table 1 Comparison of TWCM methods (Note: the more symbol “★”, the better).

Methods	Sensors/signals	Accuracy	Efficiency	Installability	Cost
Direct method	Laser, vision, et al.	★★★	★	★	★★★
	Force	★★	★★★	★	★
	Vibration	★★	★★★	★★	★★
Indirect method	Current	★	★★★	★★	★★★
	AE (Acoustic Emission)	★★	★★★	★	★★
	AS (Audible Sound)	★	★★★	★★★	★★★

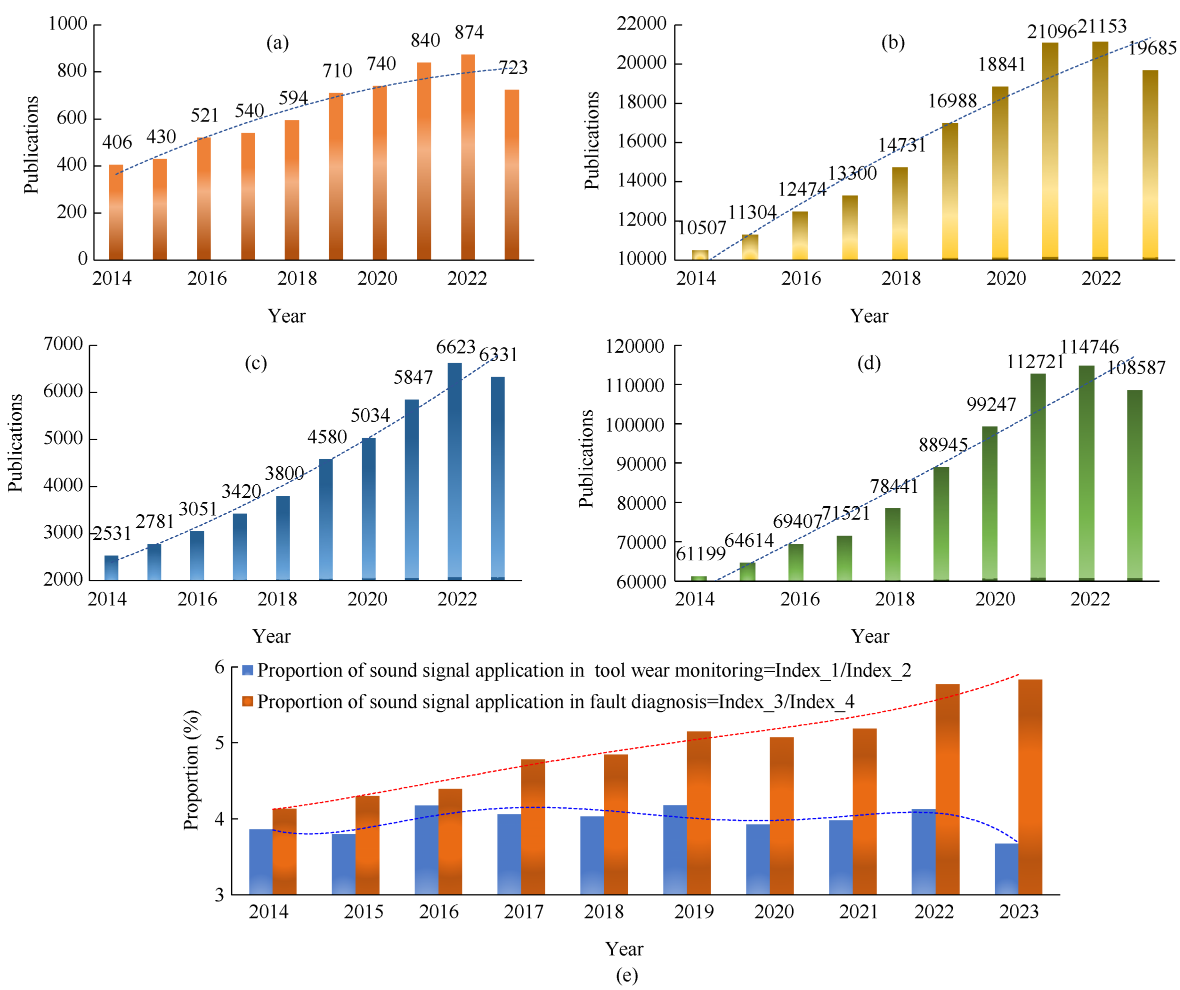


Fig. 1. Publications about sound-based monitoring in the Web of Science database:(a) Index_1: TS=("tool") AND ("wear" or "condition" or " monitoring " or "life") AND ("sound" OR "audio" OR "acoustic" OR "audible" OR "noise") NOT("emission"); (b)Index_2: TS= ("tool") AND ("wear" or "condition" or " monitoring " or "life"); (c)Index_3: TS= ("monitoring" or "fault diagnosis") AND ("sound" OR "audio" OR "acoustic" OR "audible" OR "noise") NOT("emission"); (d) Index_4: TS=("monitoring" or "fault diagnosis")

search equation was Index_2: TS= ("tool") AND ("wear" or "condition" or " monitoring " or "life").

Fig. 1(c) was the AS-based fault diagnosis, and the search equation was Index_3: TS= ("monitoring" or "fault diagnosis") AND ("sound" OR "audio" OR "acoustic" OR "audible" OR "noise”) NOT("emission").

Fig. 1(d) was about fault diagnosis without sensor limitations, and the search equation was Index_4: TS=("monitoring" or "fault diagnosis").

Furthermore, proportion of AS-based methods in tool wear monitoring field and fault diagnosis field were calculated, as presented in Fig.1(e).

The results in Fig.1(e) showed that, the application proportion of AS in fault diagnosis is constantly increasing, while the application proportion of AS in TWCM was stagnant. Considering the similarities between the two fields, more studies were needed to be carried out for the application of AS in TWCM.

3. Definition of machining AS

As a protagonist, the AS signal was first introduced. The vibration of the object produces sound signals. The sound has a frequency between 20-20000 Hz is called AS and its wavelength is 1.7 cm-17 m. The sound has a frequency below 20 Hz was called infrasound, and has a frequency above 20000 Hz was called ultrasonic.

In the physical view, AS is a physical longitudinal wave phenomenon, that is, the vibration of air molecules around the vibration source forms a dense longitudinal wave propagating mechanical energy, which continues until the vibration disappears. Therefore, AS has the same characteristics of general waves, including reflection, refraction and diffraction.

In the signal field, AS is a time-domain random signal. Its basic parameters are frequency, intensity, and phase. Frequency is the number of vibrations per second and valued by Hertz (Hz). Intensity is proportional to the vibration amplitude and its unit is decibels (dB), which reflected the sound strength. Phase refers to the position of the sound wave at a specific moment and its unit is Angle (degree), which reflect signal waveform.

In conclusion, AS is longitudinal wave traveling through the air. Its representation could learn from the description of general waves: frequency, amplitude and phase. The only difference is that the parameter “amplitude” is replaced with sound pressure level (SPL). The full representation of AS was listed in Table 2. For example, to describe the AS produced by different machining process, the average SPL can be used, as presented in Fig.2 [37].

Table 2 Representation of AS.

Parameters	Units	Comment
Frequency (f)	Hz	Number of vibrations per second
Wavelength (λ)	m	$\lambda=c/f$, c: wave velocity
Sound pressure (SP)	Pa	1Pa=1N/m²
Sound pressure level (SPL)	dB or dBA	SPL=20·lg(SP/SP0) SP: Measured sound pressure SP0: Reference sound pressure

4. Generating mechanism of machining AS

In order to get a deeper understanding of cutting AS signals, its generation mechanism was discussed through physical properties and practical experiments. From the view of physical properties,

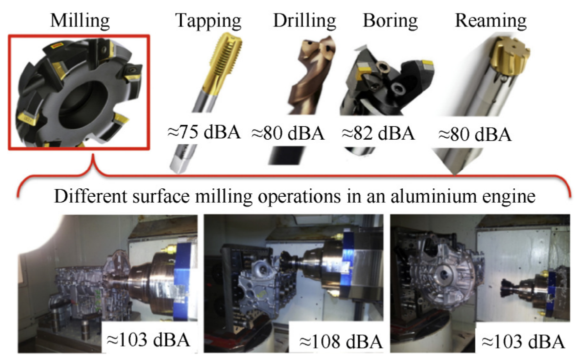
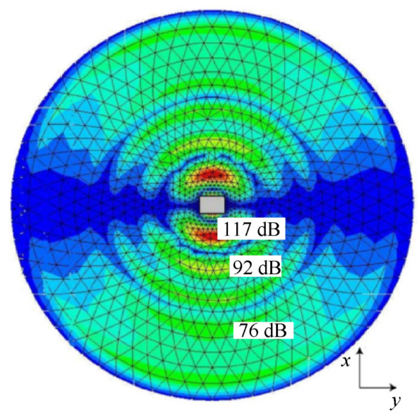
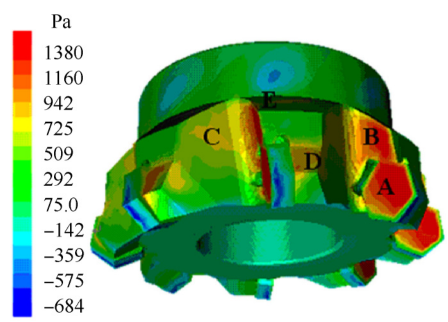


Fig. 2. Average sound pressure level emitted by various cutting technologies.[37]

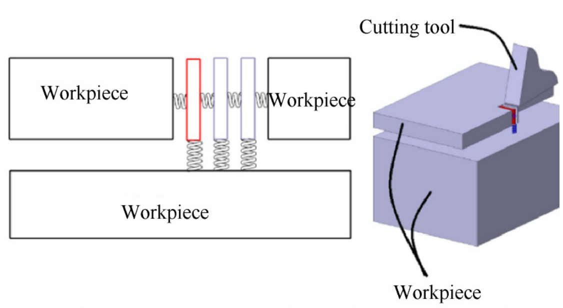
Sampath et al. [38] built an acoustic finite element model by translating the cutter-workpiece vibration into the sound pressure field in the vicinity of the cutter, Fig.3 (a). Then, Ji and Liu [39] developed a CFD simulation model to investigate the aeroacoustics AS generation and propagation by the idling face milling cutters, Fig.3 (b). Hu et al.[40] establish the combined prediction model of AS based on



(a) Radial sound pressure field around the workpiece vibrating[38]



(b) Pressure distribution on the surface of cutter[39]



(c) Equivalent spring system to describe sound generated through the deformation mechanism[41]

Fig. 3. Generating mechanism of machining AS.

force-thermal-vibration multi-feature fusion. Differently, Nourizadeh et al. [41] investigated different AS generation mechanisms during turning by practical experiments Fig.3 (c). The results showed that the AS generated through the tool holder vibration will result in a low-frequency signal, while AS generated by friction mechanism was a high-frequency signal. However, AS generated through the metal deformation produces a mid-range frequency signal.

As had been reported [42] (see Fig.4), the cutting AS was composed of multi-source signals such as chip deformation, tool-workpiece friction, tool vibration, workpiece vibration, machine tool noise, environmental noise, etc. The multi-source signal frequency bands are superimposed on each other, and the sound wave will produce reflection, diffraction and accompanied by reverb phenomenon when it meets the spindle, workbench, inner wall and other structures in the closed space of the machine tool. As a result, the monitoring sound signal has the characteristics of strong noise.

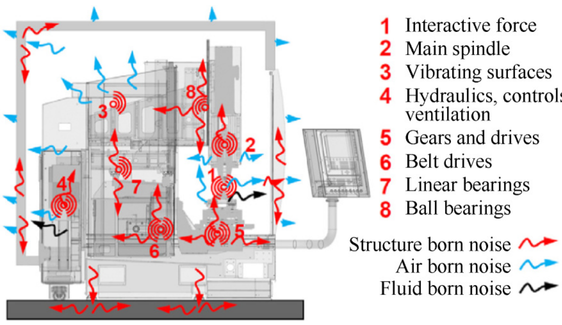


Fig. 4. Noise generation, transmission, radiation for milling machines.[42]

In conclusion, the physical model was mainly applicable to vibration induced AS with definite dynamic model, but it is difficult to apply to environmental noise. The practical experiment method relies on a large number of test data, and cannot consider the influence of tool structure and milling parameters. Therefore, the mathematical model of cutting AS signal with the input of tool structure, cutting parameters, tool wear state and the environmental noise is still needed to be further studied.

5. Research progress of key technologies

The main work about TWCM-AS is to build the relationship between the AS signals and the tool wear conditions. It includes 4 steps and corresponds to 4 key technologies, namely, acquisition of AS signals, denoising of AS signals, feature extraction of AS signals, and decision-making algorithm.

5.1 Acquisition of AS signals

The AS signals were collected by microphone sensors [43]. Important features for the microphones include frequency response, sensitivity and directionality. Frequency response determined the measurement frequency range. Generally, a higher sensitivity can increase the measurement accuracy, but will narrow down the measurement range and reduce the stability.

Considering that AS is longitudinal wave that traveled through the air and may have reflection, refraction or diffraction phenomena during the transmission, the layout of microphone sensors was important for AS signal collection. Normally, the closer the sensor is to the cutting area, the better signals would be collected. However, in order not to interfere with the cutting process, microphone sensors had to mounted long away from the cutting area [44], or even outside the machine tool [45]. Some typical microphone types used for AS signal collection and their sampling rate and sensor layout were presented in Table 3.

5.2 Denoising of AS signals

Low signal-to-noise ratio (SNR) is a prominent problem for milling AS signals. Thus, lots of works had been carried out to improve the SNR of the collected AS. Denoising methods could be divided into 2 categories according to different denoising principles, namely passive denoising method and initiative denoising method, as listed in Table 4.

- **Passive denoising method**

The passive method aimed to decompose and screen the original signal based on signal processing theories. It can be further divided into filtering method and blind source separation (BSS) method.

Filtering method is usually used to suppress background noise, including classical filtering methods such as high-pass and low-pass [61], wavelet threshold [49], adaptive filter [62], and Welch's method [67]. This method is difficult to remove the background noise of the same frequency as the target signal and the transient noise generated by irregular events. Anderson and Dias [61] used high-pass and low-pass filters to remove background noise. However, it is difficult to remove background noise with the same frequency as the target signal. Zhou et al.[49] employed the wavelet threshold de-noising algorithm to denoise the sound signals. The wavelet db3 was selected as the wavelet basis, the maximum-min principle was used to select the threshold, see Fig.5. Zafar et al. [62] used a feedforward neural network as an adaptive filter to reduce the background noise, and a novel autoregressive moving average (ARMA)-based algorithm is proposed to reconstruct the filtered signal. An average increase of 71.3% in signal-to-noise ratio (SNR) is found before and after signal reconstruction. Ferguson et al. [67] use Welch's method to reduce noise in the estimated power spectra in exchange for reducing the frequency resolution.

The BSS method [54-56, 63] is mainly used to suppress random noise. However, it was limited due to various sound components collected in actual processing, and many of them are interdependent. Li et al [54] proposed a WPT-ECBCA-MSST blind source separation method to separate source signals from noise. The raw multi-channel audio signals are firstly decomposed into multiple wavelet sub- bands using WPT. Then, an ECBCA (Fig.6) is used to separate source signals from the wavelet sub-band signals. and, the separated source signals are decomposed into time-varying oscillatory components using a multivariate synchro squeezing transform (MSST) in order to denoise. Li et al. [55] denoise the sound signal by two steps. The background noise was firstly eliminated by a bandpass filter and then the most useful source component related to the tool wear degree was separated by dependent component analysis DCA. Andrés Sio-Sever et al. [56] applied an ICA blind source separation algorithm to separate the machining sound and the background noise. Once the rotation that obtained the maximum kurtosis in an input signal was obtained, it was separated and considered as the background noise, picking up the signal with minimum kurtosis as the machining signal. Ubhayaratne et al. [63] utilized SBSS to extract the audio signal of the stamping operation to be recovered from the mixed signals from the other processes.

- **Initiative denoising method**

The initiative denoising method [64, 65] integrates the hardware design of multi-microphone wind signal acquisition system, and makes full use of the distance between each microphone and the sound source to reconstruct the signal, and realizes the suppression

Table 3 Types of microphone sensors and their layout.

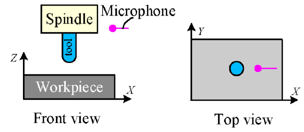
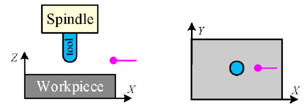
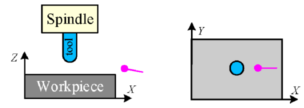
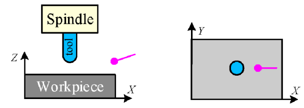
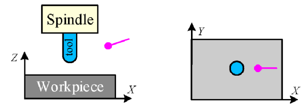
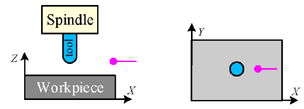
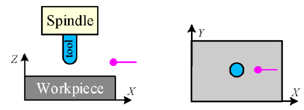
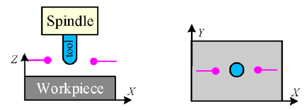
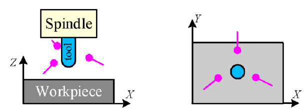
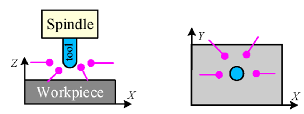
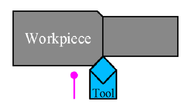
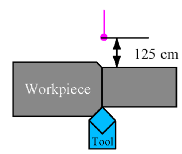
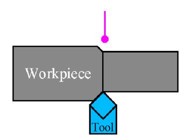
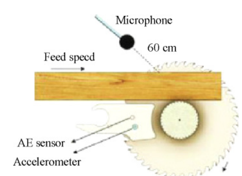
Microphone types	Sampling rate	Applications	Sensor layout	Reference
Behringer (ECM-8000)	51.2 kHz	Milling		45
PCB Piezotronics (130E21)	50 kHz	Drilling		46
Brüel & Kjær (4957)	32768 Hz	Micromilling		47
BSWA TECH (MPA201)	10240 Hz	Milling		48
GRAS Sound & Vibration (46AE)	12 kHz	Milling		49
GRAS Sound & Vibration (46AE)	10240Hz	Milling		50
GRAS Sound & Vibration (40PH)	25.6kHz	Milling		51
Brüel & Kjær (4189-A-021)	64.1kHZ	Milling		52
ECOOPRO (EO-200)	44.1kHz	Milling		53-55
BSWA TECH (MPA201)	25.6kHZ	Milling		56
Hangzhou Aihua (AWA14423)	64kHz	Turning		57
PCB Piezotronics (130E21)	50 kHz	Turning		44
PCB Piezotronics (130D20)	44.1 kHz	Turning		58, 59
PCB Piezotronics (378B02)	50 kHz	Sawing		60

Table 4 Denoising methods of AS signals.

Passive method	Filtering	High-pass, low-pass [61]
		Wavelet threshold [49]
		Adaptive filter [62]
	Blind source separation	Extended convolutive bounded component analysis (ECBCA) [54]
		Dependent component analysis (DCA) [55]
		Independent component analysis (ICA) [56]
		Semi-blind signal separation algorithm (SBSS) [63]
Initiative method	Linear layout [64]	
	Spherical layout [65, 66]	

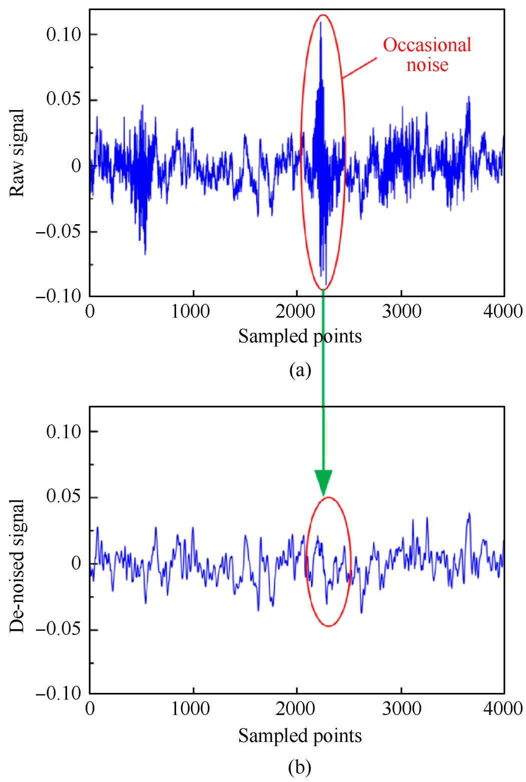


Fig. 5. De-noising effect of occasional noises based on Wavelet Transform Modulus Maxima.[49]

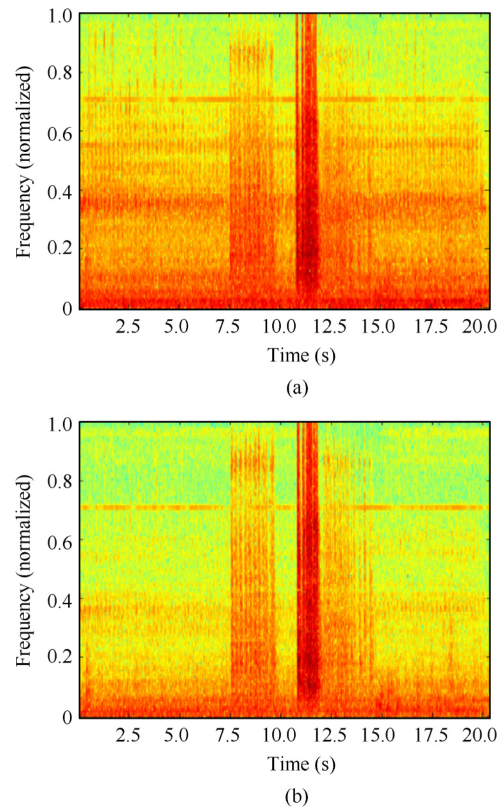


Fig. 6. Time-frequency spectrum generated by (a) STFT and (b) ECBCA.[54]

of non-stationary noise, see Fig. 7. Huang and Lu [64] designed a microphone array integrated with Wiener filter to reduce the noise effect and improve the system performance. The microphone array was built by three microphones, which were installed 50 mm away from the cutting point. The distance between microphones was set as 60 mm. The results shown that it could not only reduce the noise effect more efficient in the overall frequency range, but also minimize the distortion for the filtered signal compared to the noise-free signal. Shaffer et al. [65] designed a 32-element spherical microphone array to monitor end milling operations, which could eliminate background noises and isolating machines once the acoustic locations of those machines are known.

- **Summary**

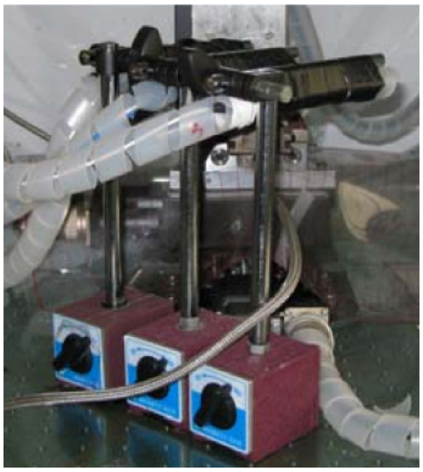
Because of the multi-source and multi-frequency characteristics of AS, the passive method is difficult to apply in the actual machining environment. The initiative method by using microphone array had more advantageous. However, the current research focuses on the free sound field, without considering the complex propagation mechanism of sound wave reflection and diffraction in the closed space of machine tools.

5.3 Feature extraction of AS signals

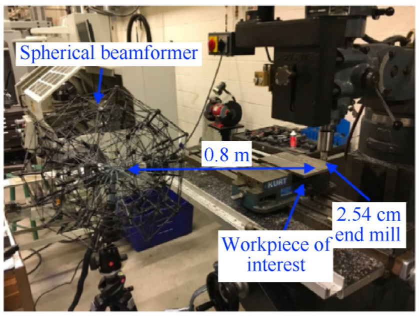
Since the AS signal collected from the sensor is relatively high sampling frequency and the original data is relatively large, each sample may contain tens of thousands of data. It is unrealistic to use these data as input to monitor the tool wear. Therefore, it is necessary to carry out feature extraction work to extract dozens or several features that are strongly related to tool wear from tens of thousands of original data. Feature extraction methods could be divided into 3 categories according to different construction principles, namely statistical features, deep learning features and construction features, as listed in Table 5.

- **Statistical features**

Statistical features are extracted based on statistical method, including maximum value, minimum value, root mean square value, et al. The statistical sources include time-domain signals [50, 68], frequency-domain signals [50, 54, 68-72] and time-frequency domain signals [45, 50, 73, 74]. The statistical features have clear physical significance, but it is difficult to cover the deep features of the sound signal that strongly associated with tool wear. Some representative studies are



(a) Linear layout [64]



(b) Spherical layout [65, 66]

Fig. 7. Arrangement of microphone array for initiative denoising method.

listed as follows.

Zhou et al. [68] chosen 14 statistical feature parameters, including 7 parameters in the time domain and 7 in the frequency domain. Li et al. [54] extracted eight statistical features (i.e., max, min, mean, median, moment, skewness, kurtosis, and standard deviation) in the time-frequency domain (Fig.8). Liu et al. [45] extracted 6 statistical of WPD coefficients, including root mean square (RMS), average (AVG), standard deviation (STD), max value, kurtosis, and skewness. The results shown that the max value of the WPD coefficients had the most significant correlation with the frank wear defined by ISO 8688.

- **Deep learning features**

Deep learning features are extracted based on deep learning algorithm. Generally, high dimensional eigenvalues are extracted by deep learning algorithm with the transformed time-frequency domain image as input. And CNN is often used because of its advantages in the field of image processing. Li et al. [55] and Cooper et al. [75] employed CNN deep learning model to find the inner connection between the image feature maps and the tool wear degree, see Fig.9. The images were Time-Frequency Domain images produced by applying a STFT to the sound signals. Deep learning features can mine tool wear information from sound signals, but it requires high-quality big data samples, and the "black box" feature of deep learning leads to insufficient reliability and applicability of extracted features.

- **Construction features**

Construction features are extracted based on special signal transformation or combined several methods. It include LPCC [76], MFCC [77, 78], SSA [79], DWT [51, 52, 80], HE [49], envelope energy features & statistical features & spectral power features [47], statistical features &energy features [54], et al. Some representative studies are listed as follows.

Ai et al. [76] calculated Ten-order LPC of the milling sound signal and then 12-order LPCC. Parts of the calculated LPCC values were used to analyze the relationship between each order component of LPCC and the flank wear of the tools. The results shown that the characteristic components associated with tool wear are mainly concentrated in the sixth-, seventh- and eighth-order components of LPCC. Zhou et al. [49] employed the Holder Exponents (HE) to estimate the singularity of signals that treated by Wavelet Transform. The results shown that the Means, Standard deviations, Minima of estimated HEs and Quantities of singular points are found most correlated to tool conditions. Gomes et al. [47] extracted 125 features related to statistical analysis, time domain and frequency from the raw signals of sound, including 8 statistical features, 39 spectral Power Features in pre-defined frequency bands and 78 envelope energy features in pre-defined frequency bands. Li et al. [54] built multiple features, including eight statistical features extracted in the time-frequency domain and an energy feature. The energy feature was extracted by summing up the energy-amplitude in the range of 0-1400 Hz. Madhusudana et al. [51] extracted 8 DWT features from the acquired sound signals to diagnose the fault of the face milling tool.

- **Summary**

The shallow properties of statistical features and the "black box" properties of deep learning features lead them have limitations in accuracy, robustness and applicability. Construction features are one of the main development directions. For low signal-to-noise ratio sound signals, construction features with strong robustness to noise are particularly critical, but there are few reports on this problem.

Table 5 Feature extraction methods of AS signals.

Statistical features	Time-domain [50, 68]
	Frequency-domain signals [50, 54, 68-72]
	Time-frequency domain signals [45, 50, 73, 74]
Deep learning features	Convolutional neural network (CNN) [55, 75]
Construction features	Linear Prediction Cepstrum Coefficient (LPCC) [76]
	Mel-Frequency Cepstral Coefficients (MFCC) [77, 78]
	Singular Spectrum Analysis (SSA) [79]
	Discrete Wavelet Transformation (DWT) [51, 52, 80]
	Holder Exponent (HE) [49]
	Envelope energy features & statistical features &spectral Power Features [47]
	Statistical features & energy features [54]

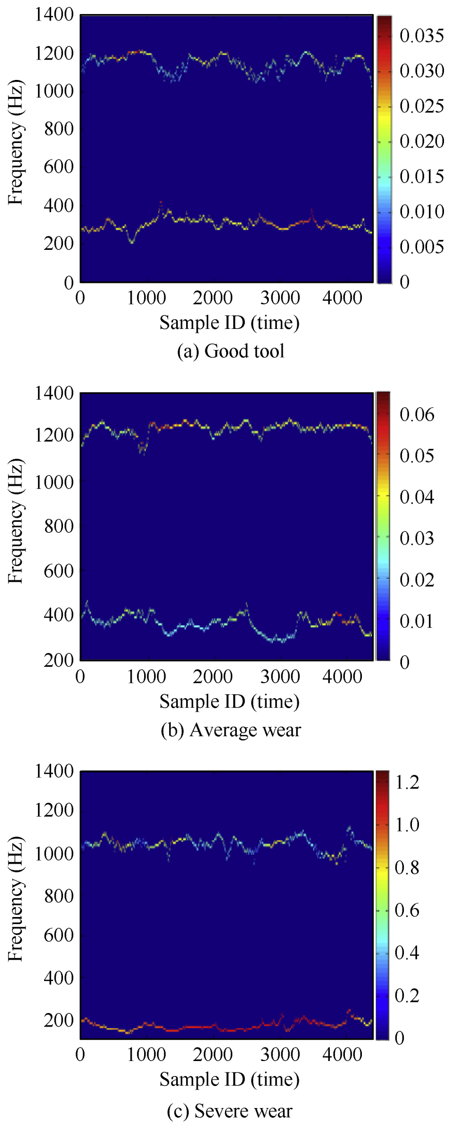


Fig. 8. Time-frequency spectrums. [54]

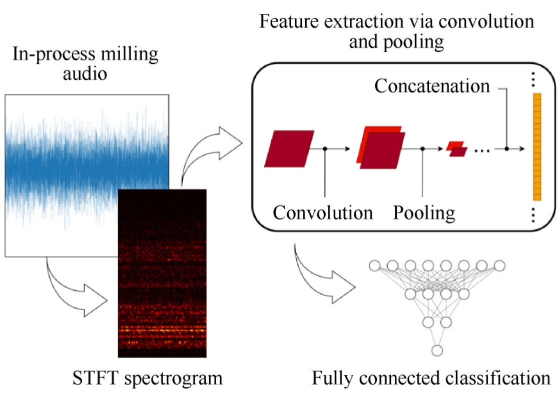


Fig. 9. Flowchart of convolutional neural network-based tool condition monitoring. [75]

5.4 Decision-making algorithm

The nature of tool wear monitoring algorithm is to establish a mapping relationship between monitoring sound signal and the tool wear, which can be divided into two categories according to whether deep learning is involved, namely the traditional method and the deep learning method, as listed in Table 6.

- **Traditional method**

The traditional method firstly extracted the feature of the original monitoring signal by the technology of feature engineering, and then the learning algorithm is trained by the feature value and the corresponding wear label. It included LRA [81] , ANN [45, 73, 82-85] , ELM [68, 86] , SVM [47, 49, 54, 87, 88] , HMM [50, 89] , KNN [52] , GPR [67], BPNN [90], NNR [91], KCA [92], Bayesian network [93], RFC [94] , et al. The traditional method is very sensitive to the tool structure, milling parameters and other variables, so it is difficult to meet the actual machining requirements. Some representative studies are listed as follows.

Liu et al. [45] proved that cubic curve regression model and the ANN have good accuracy for tool wear prediction based on sound signal, and their prediction errors were 8.59% and 7.20%, respectively. Gomes et al. [47] used SVM to monitor tool wear in micro milling process with vibration and sound signals, and obtained a classification accuracy of up to 97.54%. Li et al. [54] discussed four classifiers, including CART, random forest (RF), KNN and SVM for tool wear monitoring with audio signals. The best overall accuracy was obtained by SVM. Yan et al. [50] established a condition-adaptive hidden semi-Markov model (CAHSMM) to describe the evolution of tool wear, in which the accelerated failure time model (AFTM) embedded with Taylor tool life equation is utilized to determine the state transition probabilities that are strongly dependent on cutting parameters and duration time, see Fig.10.

- **Deep learning method**

Deep learning methods combined feature extraction with model training. It included image-learning algorithms, such as CNN [53, 55, 75, 95, 96] , SNN [28,97], TAKELM [68] , Image Transfer Learning [98] , DNN [77], unsupervised-learning algorithms generative adversarial network [66] and DCNN [99] .The "black box" nature of the deep learning decision-making process results in reduced accuracy and reliability when the monitoring signal contains a large number of process environment interference. This method has achieved a series of achievements in the academic world, but few reported in practical applications. Some representative studies are listed as follows.

Zhou et al. [68] developed a TAKELM method, which enhanced the learning of features associated with complex nonlinear data, and the use of two angle kernel functions without hyperparameters avoided the complications associated with the preset hyperparameters employed in conventional kernel functions. Li et al. [55] proposed an ensemble CNN detection model, which was able to establish a reliable connection between the audio signal features and the tool wear conditions. Kothuru et al. [53] carried out a comparative analysis between SVM and CNN. The proposed SVM and CNN models have shown a significant overall prediction accuracy of 98% and 96.3% in tool wear monitoring based on sound signals. Cooper et al. [75] proposes a 2DCNN deep learning architecture for tool condition classification, and the classification accuracy was as high as 99.5%. Ntalampiras [97] presented a SNN composed of convolutional layers and enhanced SNN's classification ability by an appropriately designed data selection scheme, so that the obtained predictions are interpretable, see Fig.11.

- **Summary**

Although many mapping models between sound signal and tool wear have been established, but the model accuracy was improved by adjusting model hyperparameters and increasing model complexity, which resulted in unclear decision-making process. Especially for acoustic signals with low signal-to-noise ratio, it is difficult to obtain monitoring models with high precision and strong robustness.

Table 6 Decision-making algorithms.

Traditional method	Linear regression algorithm (LRA) [81] Artificial neural network (ANN) [45, 73, 82-85] Extreme learning machine (ELM) [68, 86] Support vector machine (SVM) [47, 49, 54, 87, 88] Hidden Markov models (HMM) [50, 89] k-Nearest Neighbor (KNN) [52] Gaussian process regression (GPR) [67] BP neural network (BPNN) [90] Neural network-based regression (NNR) [91] K-means clustering algorithm (KCA) [92] Bayesian network [93] Random forest classifier (RFC) [94]
Deep learning method	CNN [53, 55, 75, 95, 96] Siamese neural network (SNN) [97,28] Two-layer angle kernel extreme learning machine (TAKELM) [68] Image Transfer Learning [98] Time-series-learning algorithms deep neural network (DNN) [77] Unsupervised-learning algorithms generative adversarial network [66] Deep convolutional neural network (DCNN) [99]

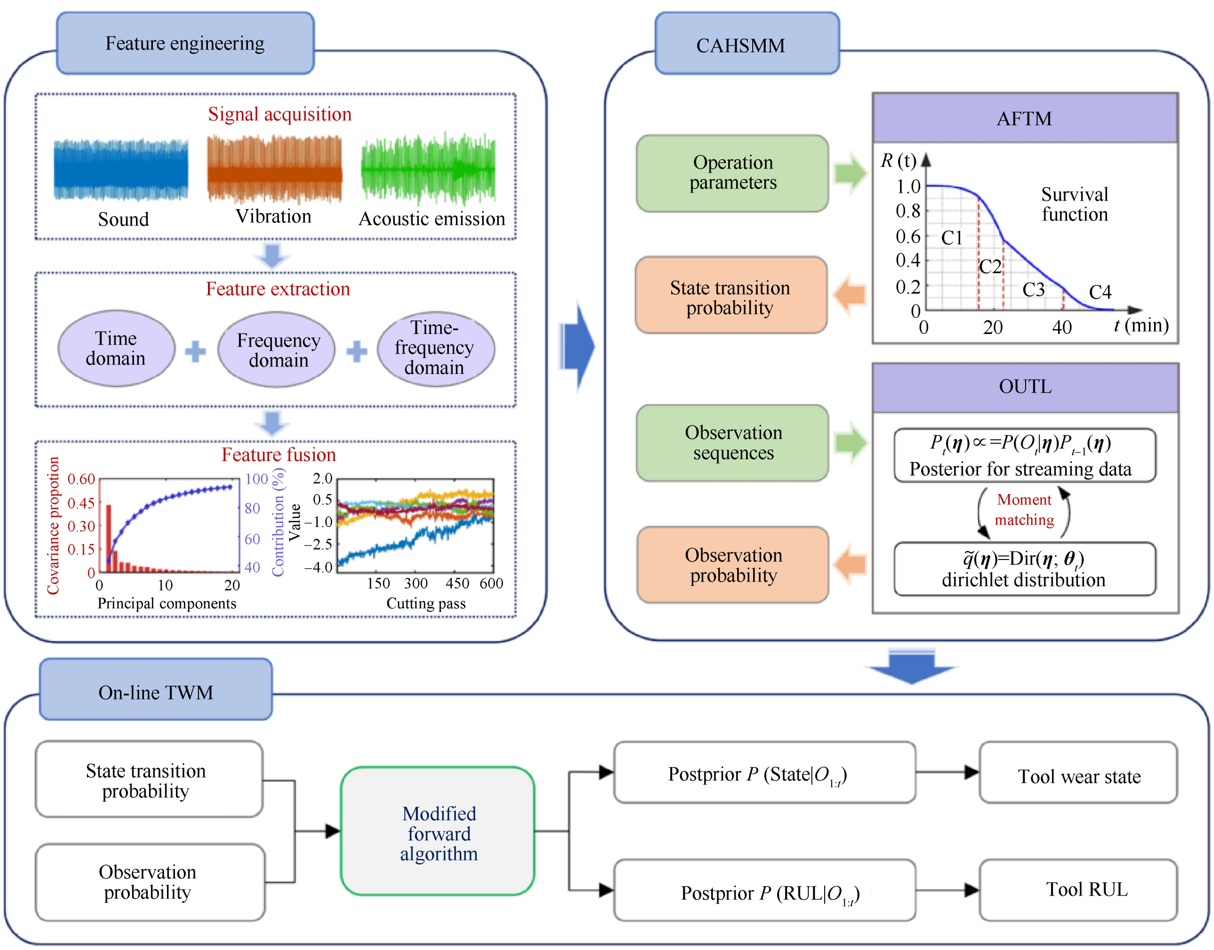


Fig. 10. Frame of condition-adaptive hidden semi-Markov model (CAHSMM). [50]

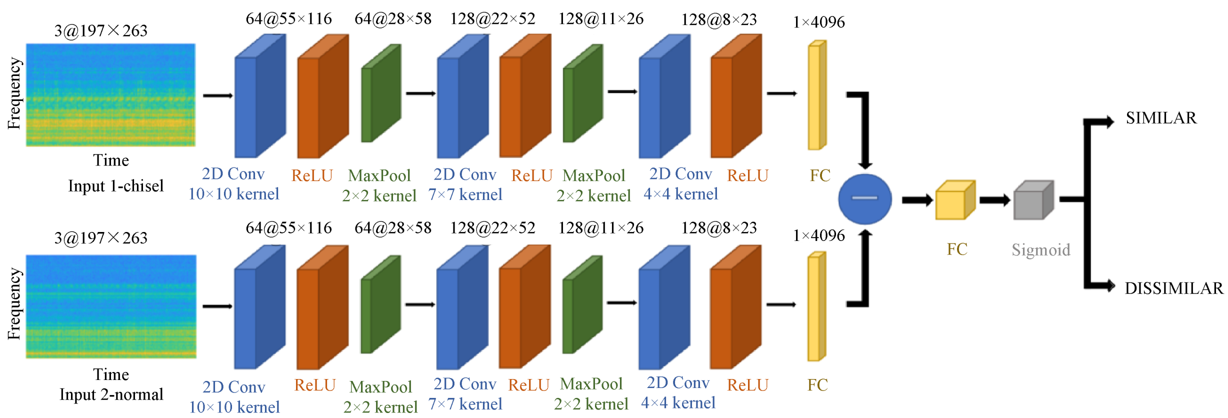


Fig. 11. one-shot learning scheme using Siamese neural networks. [97]

6. Research prospects

(1) Datasets for TWCM-AS

Physical-based method was hard for TWCM-AS, because the generation mechanism of cutting AS signals were too complex to establish physical models. Therefore, data-driven method was a significant way or may be a predominant way for TWCM. As was well known, datasets play a vital role for data-driven method. However, the reported dataset about TWCM, such as PHM2010 [100] NASA [101] and NUAA_Ideahouse [102] did not include AS signals. In the field of machine abnormal sound detection, there exist datasets MIMII [103] and ToyAD-MOS [104] that included AS signals, but they could not be used for TWCM, because the datasets were just concerned the machine itself, rather than the cutting process. Thus, datasets including AS signals and tool wear labels should be established.

(2)Initiative denoising system for AS collection

Because of the multi-source and multi-frequency characteristics of cutting noise, the passive denoising method would have poor performance in practical machining environment, which leaded to that low signal-to-noise ratio (SNR) become a main obstacle for TWCM-AS. The initiative noise reduction method by using microphone array would be a promising solution. However, current researches mainly focused on free sound field, and there were little initiative denoising methods for enclosure sound field, which should consider the complex propagation mechanism of reflection or diffraction phenomena in the closed space of machine tools.

(3) Feature extraction of AS signals

Feature extraction of AS signals was still a significant work for TWCM-AS, although the deep learning algorithm did not require this step. Because on the one hand, features were the bridge between AS and tool wear, which will help to understand the tool wear evolution process. On the other hand, appropriate features will reduce the complexity of the monitoring model operation and meanwhile improve its accuracy, which was helpful for improving the efficiency, robust and practical application of TWCM. Traditional feature extraction methods, such as statistical features and deep learning method, could be applied for AS signals. Considering the abundance of information contained in the sound signal, more special features used for similar field could be further utilized, for example, voiceprint, pitch frequency, per-channel energy normalization, et al.

(4) Interpretable Decision-making algorithm

A clear decision-making process was necessary for the practical application of TWCM-AS. Deep learning algorithm will achieve a good accuracy as long as training by a large amount of data, but it cannot show the mathematical relationships between AS signal and tool wear and cannot reveal the decision-making process, which would reduce the monitoring credibility. Therefore, it is necessary to further develop a clear mathematical relationship between AS signal and tool wear, or provide an explicit decision-making process. To this end, interpretable decision-making algorithm that embedded mechanistic knowledge or generate mathematical expressions should be studied, for example, Sparse Identification of Nonlinear Dynamical systems (SINDys), Physics-informed Neural Networks (PINNs), et al.

7. Conclusions

AS signal is a prospective strategy for the utilization of TWCM in practice. Many TWCM-AS methods have been discussed in the past years. As their work always focused on part of the monitoring system, this paper presented a systematic review from research progress of four key technologies, including acquisition, denoising, feature extraction and decision-making algorithm.

Furthermore, four research prospects were further put forward: (1) datasets for TWCM-AS was needed, (2) initiative denoising system for AS collection should be designed, (3) some special feature extraction methods for AS signals should be attempted, and (4) interpretable decision-making algorithm should be employed.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 62203193, 51605207).

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