Application of Bispectrum Diagonal Slice Feature Analysis in Tool Wear States Monitoring

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Title page

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Abstract

Tool wear is unavoidable during machining, which is one of the most common tool failure modes. It is significant to evaluate the tool state quickly and effectively for timely tool change strategy. The cutting vibration signals after tool wear show strong non-Gaussian characteristics. Higher order spectrum is a powerful tool for analyzing the non-Gaussian characteristics of signals, and can restrain noise and provide more information than classical power spectrum analysis. This paper presents a milling tool wear state monitoring method based on higher order spectrum entropy. Due to the large amount of calculation of bispectrum, bispectrum diagonal slice is investigated. And the diagonal slice spectral entropy is proposed as tool wear indicator to monitor tool state. To verify the proposed method, cutting vibration signal of CNC machining center were collected and analyzed. The experimental results showed that the proposed approach can effectively monitor and diagnose the tool state, and has good robustness. It is feasible and effective for on-line monitoring milling tool wear.

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Declarations

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Conflicts of interest/Competing interests

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Availability of data and material

The datasets used in the study are available from the corresponding authors according to reasonable request.

Code availability

The code analyzed in the study are available from the corresponding author according to reasonable request.

Ethics approval

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Consent to participate

Not applicable.

Consent for publication

Not applicable.

Authors' contributions

Bin Yang: Methodology, experimental design, data processing and analysis, writing-original draft preparation. Min Wang: Funding acquisition, project administration, supervision, review and editing article. Tao Zan: Providing lab facilities, experimental design. Xiangsheng Gao: Review and editing article. Peng Gao: Investigation, reviewing article.

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Abstract: Tool wear is unavoidable during machining, which is one of the most common tool failure modes. It is significant to evaluate the tool state quickly and effectively for timely tool change strategy. The cutting vibration signals after tool wear show strong non-Gaussian characteristics. Higher order spectrum is a powerful tool for analyzing the non-Gaussian characteristics of signals, and can restrain noise and provide more information than classical power spectrum analysis. This paper presents a milling tool wear state monitoring method based on higher order spectrum entropy. Due to the large amount of calculation of bispectrum, bispectrum diagonal slice is investigated. And the diagonal slice spectral entropy is proposed as tool wear indicator to monitor tool state. To verify the proposed method, cutting vibration signal of CNC machining center were collected and analyzed. The experimental results showed that the proposed approach can effectively monitor and diagnose the tool state, and has good robustness. It is feasible and effective for on-line monitoring milling tool wear.

Keywords: Milling; Higher order spectrum; Diagonal slice spectral entropy; Tool condition monitoring

1 Introduction

As a key process in the manufacturing industry, machining has an important position in modern production. Tool is one of the most important machining elements in machining, and is the direct executor. In the process of cutting, the tool contact with the workpiece, due to the role of friction, chip and the cutting heat, tool is prone to wear or breakage. The tool state changes will lead to the variation of cutting force [1, 2], cutting temperature [3, 4], surface roughness [5, 6], and even generate cutting chatter [7, 8] or causes other serious consequences, which will affect the safe operation of the whole machining system. Therefore, tool condition monitoring has attracted extensive attention in the field of intelligent manufacturing. It is significant to accurately monitor tool wear progression in order to take timely tool change strategy in machining process.

In the traditional machining process, tool state is judged by the color and shape of chip, the noise during the machining process, or according to the machining time, or disassembling the tool between the processing procedures to measure the extent of wear. These methods are either closely related to the experience of the machining staff or require downtime for off-line measurement, which has become an important bottleneck restricting the development of the manufacturing industry. It is necessary to develop an effective method to detect tool wear state in real time.

The sensor-based indirect measurement approach provide a way for online tool wear state

monitoring. The cutting force is the most effective and accurate tool wear monitoring method [9-11]. However, the method requires the installation of force sensors under the work piece which can be cumbersome and costly. The vibration-based monitoring method is widely used in practice due to the sensor of convenient installation and cost effective [12-14]. Milling is an interrupted machining, which results in nonstationary signal. Moreover, with the increasing of the tool wear degree, the cutting vibration signal gradually shows obvious non-Gaussianity originated from the increased friction between the tool and workpiece. The frequency domain power spectrum (PS) analysis method based on second-order statistics is one of the most commonly used signal analysis methods in the condition monitoring and fault diagnosis. Nevertheless, PS analysis has obvious limitations and deficiencies, which is only for stationary signals and sensitive to the noise. Furthermore, the second-order statistics cannot provide the phase information of the signal. Therefore, the traditional PS analysis method is difficult to solve non-Gaussian phenomenon and noise suppression in the process of tool wear.

Higher order spectrum (HOS) is a signal processing method based on high-order statistics, which is defined as the multidimensional Fourier transform of high-order cumulant [15, 16]. HOS can make up for many shortcomings of the second-order statistics, it is a powerful tool for detecting nonlinear, non-Gaussian system, and preserving the phase information of signal [17]. HOS methods have been widely used in nonlinear system identification [18, 19], biomedical signal processing [20], speech signal recognition [21, 22], radar and sonar signal processing [23, 24], condition monitoring and fault diagnosis [25-28]. Bispectrum is the most commonly used high order spectrum, which is the lowest order of the HOS, the third-order statistics of the signal. However, the computational cost of bispectrum is higher and the physical meaning is difficult to interpret. Additionally, tool wear is a slow changing process, quantitative evaluation of tool wear is also a challenging problem.

In this paper, a milling tool condition monitoring method based on bispectrum diagonal slice entropy is proposed. The application of bispectrum diagonal slice and diagonal slice spectrum entropy based on cutting vibration signal were investigated to detect and monitor tool wear states. And the application of the method for different cutting condition has been discussed. The contents of this paper are organized in the following way. In Section 2, the theoretical methods are introduced. In Section 3, the experimental setups are described for validating the proposed method. In Section 4, the main results are discussed. Finally, the conclusion of this work are given in Section 5.

2 Theoretical Methods

2.1 Bispectrum

The third-order spectrum of the HOS is called bispectrum, which is the lowest order in the HOS, and has all the advantages of the HOS. Bispectrum provides the third-order statistic information of the signal, can capture the phase information between the frequency components, effectively restrain Gaussian noises and improve the signal-to-noise ratio. The bispectrum can be regarded as the decomposition of signal skewness in the frequency domain [29], so it can describe the asymmetric and nonlinear characteristics of the signal, and characterize the degree of deviation from the Gaussian distribution of the stochastic process. The bispectrum is the two-dimensional Fourier transform of third-order cumulant function. If $x(t)$ is a zero mean stationary random process, its third-order cumulant is defined as:

$$C_{3x}(\tau_1, \tau_2) = E\{x(t)x(t+\tau_1)x(t+\tau_2)\} \quad (1)$$

where $E\{\cdot\}$ denotes the expectation operator, τ_1 and τ_2 denote the time shift.

If the third-order cumulant is absolutely summable,

$$\sum_{\tau_1=-\infty}^{\infty} \sum_{\tau_2=-\infty}^{\infty} |C_{3x}(\tau_1, \tau_2)| < +\infty \quad (2)$$

The bispectrum of the signal $x(t)$ can be expressed as:

$$B(\omega_1, \omega_2) = \sum_{\tau_1=-\infty}^{\infty} \sum_{\tau_2=-\infty}^{\infty} C_{3x}(\tau_1, \tau_2) e^{-j(\omega_1 \tau_1 + \omega_2 \tau_2)} \quad (3)$$

If $x(t)$ is a finite energy signal, and its Fourier transform exists, the bispectrum can be defined as:

$$B(f_1, f_2) = X(f_1) \cdot X(f_2) \cdot X^*(f_1 + f_2) \quad (4)$$

where

$$\omega = 2\pi f \quad (5)$$

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j \frac{2\pi f n}{N}} \quad (6)$$

$X(f)$ is the discrete Fourier transform of the signal $x(n)$, $X^*(f)$ is the complex conjugate of $X(f)$.

As can be seen from the above expression, the bispectrum is a two-dimensional function of frequency variables f_1 and f_2 , which analyses the relationships between the frequency components at f_1 , f_2 and $f_1 + f_2$ [30].

2.2 Bispectrum diagonal slice

Bispectrum is a high-dimensional matrix obtained by two-dimensional Fourier transform of the third-order cumulant. The calculation of bispectrum is a bit large and time-consuming, especially for a large amount of data, which is not convenient for online identification and application [31]. Multi-dimensional functions of high-order statistics can be processed by dimensionality reduction. For the third-order cumulant, the two-dimensional function can be projected to a one-dimensional function space to reduce the calculation [32]. The bispectrum diagonal slice is introduced to solve these problems.

For a stationary random signal $x(t)$ with zero mean, its third-order cumulant diagonal slice is expressed as:

$$C_{3x}(\tau) = E\{x(t)x(t+\tau)x(t+\tau)\} \quad (7)$$

with $\tau_1 = \tau_2 = \tau$.

The bispectrum diagonal slice of the signal is defined as the one-dimensional Fourier transform of the third-order cumulant diagonal slice:

$$B_s(f) = \sum_{\tau=-\infty}^{\infty} C_{3x}(\tau) e^{-j2\pi f \tau} \quad (8)$$

The bispectrum diagonal slice is namely diagonal slice spectrum (DSS) or 1.5-dimensional spectrum, which is actually the projection of the bispectrum onto the plane $f_1 = f_2$. DSS is a special expression of

HOS analysis and has less computation cost than other HOS analysis method [32]. Moreover, DSS retains the advantages of high-order statistical analysis. It can be summarized as follows [33]:

- (1) If a signal $x(t)$ is a Gaussian signal, its $B_x(f) = 0$. It means DSS can suppress the noise where the signal is corrupted with Gaussian noise.
- (2) If $x(t) = p(t) + q(t)$, where $p(t)$ and $q(t)$ are independent and $q(t)$ is the Gaussian stationary process, then $B_x(f) = B_p(f)$. It indicates that DSS can be utilized to separate independent non-Gaussian signals and Gaussian noise.
- (3) The DSS can effectively detect quadratic phase coupling (QPC) of a signal.

2.3 Diagonal slice spectrum entropy

Information entropy proposed by Shannon is a measure of the uncertainty or complexity of the information. If the probability of the discrete random variable $X=(x_1, x_2, \dots, x_n)$ is $P=(p_1, p_2, \dots, p_n)$, and

$\sum_{i=1}^n p_i = 1$, then the information entropy of X is defined as:

$$H = -\sum_{i=1}^n p_i \cdot \log p_i \quad (9)$$

As for the information entropy, if the information is evenly distributed, the entropy value will be the largest; otherwise, the entropy value will be small.

By combining information entropy with DSS analysis method, diagonal slice spectrum entropy(DSSE) has defined similar to that of amplitude spectrum entropy, which can quantitatively describe the irregular variation of DSS cause by tool wear. The formulae for DSSE is given as:

$$H_s = -\sum_{f=0}^{f_s/2} p_s(f) \cdot \log p_s(f) \quad (10)$$

where

$$p_s(f) = \frac{|B_s(f)|}{\sum_{f=0}^{f_s/2} |B_s(f)|} \quad (11)$$

and $B_s(f)$ is the DSS.

2.4 The monitoring method of the tool wear states

In general, tool wear or failure state is defined based on the normal state, so it is reasonable to determine the wear state and wear detection standard according to the obtained normal state data. Hence, the samples under tool normal state are used to calculate the threshold of DSSE. According to the central limit theorem, for an unknown distribution with a certain number of samples, its confidence interval can be derived as follows [35].

$$[\bar{x} - S * \sigma, \bar{x} + S * \sigma] \quad (12)$$

where $\bar{x}$ and S are the mean value and the standard deviation of DSSE for normal state sample. When the confidence value equals $\Phi\%$, it indicates that the probability of DSSE of a sample in this interval is $\Phi\%$. In practical applications, the two commonly used confidence levels are 95% and 99%,

and the corresponding σ values are 1.96 and 2.576. Whether the upper or lower control limit is used as the threshold to detect the severe wear state of tool depends on the change trend of DSSE. If the DSSE value increases with tool wear, the upper control limit is used as the threshold; if the DSSE value decreases with tool wear, the lower control limit is used as the threshold.

3 Experiments

The milling experiment was performed on a DM1007 Machining Center (GXK1000M CNC system). The spindle motor power is 1.59KW, the spindle speed is 0-6000rpm, and the actual processing range is 240mm×165mm×240mm. Three kinds of four flutes uncoated carbide end milling cutter with different diameters were used in the experiment, two of them with 8 mm diameter and one with 10 mm diameter. The workpiece material were Cr12 die steel and 45# steel, and the size were 170mm×100mm×80mm. The three-axis piezoelectric accelerometer (YD-193) were used to measure the spindle vibration signal. The accelerometer was mounted on the spindle holder of the milling machine, as shown in Fig. 1. The directions of acceleration sensor X, Y and Z were respectively in one plane with the X, Y and Z coordinate axes of the CNC machine tool. The vibration signals were picked up by a four-channel embedded acquisition system. The data acquisition system was connected to a PC.

Fig. 1 The schematic diagram of experimental setup

The parameters of milling operation were in Table 1. The milling mode was down milling. In order to accelerate tool wear and damage, coolant was not used in the cutting process. The run-to-failure test of tool was designed.

Table 1 Milling experiment parameters

Workpiece material	Tool diameter(mm)	Speed(rpm)	Feed(mm/min)	Depth of cut(mm)	Width of cut(mm)	Metal remove rate(cm ³ /min)
Cr12 steel	8	3000	600	0.5	4	1.2
45# steel	8	3000	1000	1	4	4.0
45# steel	10	1750	1050	0.7	5	3.675

The tooth passing frequency is expressed as:

$$f_t = r \cdot N / 60 \quad (13)$$

where r is the rotate speed of spindle, N is the number of cutter tooth.

4 Results and discussion

4.1 Bispectrum analysis of milling vibration signal

In this section, the data of Cr12 steel is taken as an example for bispectrum analysis. The vibration data collected in feed direction are selected. Fig. 2 shows the milling vibration signal of different tool wear states. As shown in Fig. 2, with the proceeding of the milling process, the vibration waveforms become more regular and smoother. There are four peaks within one revolution of spindle rotation(0.02s), which correspond to four cutting edges.

Fig.2 The cutting vibration signals under different tool wear states: (a) sharp (VB=0 mm); (b) moderate wear (VB=0.162 mm); (c) severe wear (VB=0.51 mm)

The bispectrum estimate three-dimensional graph and two-dimensional contour graph of tool vibration signals under different states are show in Figs. 3-5. It can be seen that the difference of bispectrum between different wear states are obvious. When the tool is sharp, the amplitude distribution of bispectrum is relatively dispersed, the bispectrum plot shows multiple sets of peaks, such as (200 Hz, 200 Hz), (200 Hz, 400 Hz), (200 Hz, 600 Hz), (400 Hz, 200 Hz), (400 Hz, 400 Hz), (400 Hz, 600 Hz), (600 Hz, 200 Hz), (600 Hz, 400 Hz). Those bispectrum peaks are mainly concentrated in the frequency band f_1 (200-600 Hz) and f_2 (200-600 Hz). When the tool is moderate wear, the bispectrum peaks mainly appeared at (200 Hz, 200 Hz), (200 Hz, 400 Hz), (400 Hz, 200 Hz), (400 Hz, 400 Hz), and the bispectrum peaks are smaller than the sharp state. When the tool is severe wear, the bispectrum peaks (200 Hz, 200 Hz) is dominant and very large, the bispectrum peaks (200 Hz, 400 Hz) and (400 Hz, 200 Hz) become smaller and smaller, the energy becomes relatively concentrated.

Fig. 3 The vibration signal bispectrum of sharp tool ($VB=0$ mm): (a) the bispectrum three-dimensional figure; (b) two-dimensional contour figure

Fig. 4 The vibration signal bispectrum of moderately worn tool ($VB=0.162$ mm): (a) the bispectrum three-dimensional figure; (b) two-dimensional contour figure

Fig. 5 The vibration signal bispectrum of severely worn tool ($VB=0.51$ mm): (a) the bispectrum three-dimensional figure; (b) two-dimensional contour figure

4.2 DSS analysis of milling vibration signals

The bispectrum operation requires a huge computation cost and the three-dimensional graph or the contour graph are difficult to describe and interpret. Whereas the DSS requires less computation cost and is more suitable for online applications. In order to eliminate the influence of cutting conditions, DSS was normalized.

$$B_n(f) = \frac{B_s(f) - \min(B_s(f))}{\max(B_s(f)) - \min(B_s(f))} \quad (14)$$

where $B_s(f)$ is the diagonal slice, $B_n(f)$ is the normalized diagonal slice value, $\max(\cdot)$ and $\min(\cdot)$ represent the maximum and minimum values respectively.

The normalized DSS of the tool vibration signals under different states are shown in Fig. 6. From the results shown in Fig. 6, it can be observed that the amplitude of the main components of DSS changes obviously under different states, especially the 200 Hz and 400 Hz components. When the tool is sharp, the component of 400 Hz is the dominant, the other components are smaller. When the tool is moderate wear, the amplitude of 200 Hz component increases significantly. When the tool is severe wear, the amplitude of the 400 Hz component is significantly reduced, and the amplitude of the 200 Hz component becomes the dominant component. At the same time, the amplitude of the 600 Hz component gradually decreases during the whole process. The results show that the DSS can provide sufficient information to distinguish different tool states. Furthermore, DSS is more direct and simply to distinguish tool state than the bispectrum.

Fig. 6 The normalized DSS under different tool states: (a) sharp (VB=0 mm); (b) moderate wear (VB=0.162 mm); (c) severe wear (VB=0.51 mm)

Fig. 7 displays the PS analysis of the cutting vibration of different tool wear states. It has been shown that the PS calculation results are similar to the DSS method results for the same cases. However, DSS is cleaner and more visible than PS. That is because the random noise is suppressed effectively by DSS. Therefore, DSS is much better than that of the PS for detecting tool wear.

Fig.7 The PS under different tool wear states: **(a)** sharp (VB=0 mm); **(b)** moderate wear (VB=0.162 mm); **(c)** severe wear (VB=0.51 mm)

4.3 Tool wear states monitoring by DSSE

The DSSE is implemented to quantify the differences of DSS with different degrees of wear in the two-dimensional plane of amplitude-frequency. In order to better observe the trend of DSSE change, the smoothing process with moving average is carried out. Fig. 8 shows the change trend of the DSSE value. It can be observed that the DSSE value decreases gradually with tool wear. This is because the regular periodic characteristics of cutting vibration signal during wear are more significant than those under normal state. As can be seen from the figure, the whole process can also be divided into three stages. The DSSE value before the first 1500 seconds can be viewed as tool initial wear period. The decreasing trend of DSSE value slight increases from the 1500 seconds to the 2500 seconds, which indicates tool wear has entered the moderate wear period. The trend of DSSE value becomes flat after 2500 seconds, which indicates the tool wear started to be severe at that stage. Compared with DSSE, the result of power spectrum entropy(PSE) for the same conditions is shown in the Fig. 9. It can be seen that the PSE curve fluctuates greatly.

Then, how to determine the threshold based on the DSSE value becomes an important issue for quickly and effectively evaluating the state of tool. According to the threshold method described in Section 2.4, since the DSSE value with normal state is greater than the value under wear state, the lower confidence limit, $\bar{x} - S * \sigma$, is considered as the threshold for tool severe wear state detection. If the DSSE value is below the threshold value, the tool condition is estimated to be severe wear state, otherwise it represents normal state. In this study, 95% confidence level was considered. And the threshold values for this case is 4.6202 as marked in Fig. 10 by red line. Consequently, if the DSSE value of a given sample is less than the corresponding threshold value, it indicates severe wear state, otherwise represents normal state.

Fig. 8 The trend of DSSE value

Fig. 9 The trend of PSE value

Fig. 10 The vibration signal and the DSSE value: **(a)** the vibration signal of the entire cutting process after removing the air cut part; **(b)** the detection result of DSSE with threshold

The above analysis results prove that the DSSE can be used to monitor the wear progression, and threshold method can accurately determine the degree of tool wear.

4.4 Verification of the proposed method under different cutting parameters

In order to further verify the reliability of the proposed method, experiments under different cutting parameters need to be considered. The second and third sets of cutting parameters in Table 1 are used for verification. Figs. 11-15 show the experimental results for cutting parameter 2. Fig.11 shows the cutting vibration signals under different wear states. The waveform of the blunt tool has stronger periodicity than the fresh tool. Fig. 12 displays the PS of different tool wear states. The DSS of different wear states are shown in Fig.13. It is clear to show that the DSS is easy to distinguish tool state compared with PS. Fig. 14 displays the trend of PSE value. Fig.15 is the result of DSSE value. Although the PSE also shows a similar variation trend, the fluctuation is relatively large. As shown in Fig. 15(b), the DSSE drops rapidly in the first 200 seconds. This is associated with a large metal remove rate ($4.0 \text{ cm}^3/\text{min}$), which leads to rapid tool wear. The DSSE value changes smoothly after the 300 seconds, which indicates that the tool wear started to be severe. And the threshold values for this case is 1.5388 as marked in Fig. 15(b) by red line.

Fig. 11 The vibration signal of tool 2 under different wear states (Workpiece material: 45# steel; speed 3000 rpm; feed: 1000 mm/min; cutting depth: 1 mm; cutting width: 4 mm): (a) sharp (VB=0 mm); (b) moderate wear (VB=0.235 mm); (c) severe wear (VB=0.483 mm)

Fig. 12 The PS of tool 2 under different wear states (Workpiece material: 45# steel; speed 3000 rpm; feed: 1000 mm/min; cutting depth: 1 mm; cutting width: 4 mm): (a) sharp (VB=0 mm); (b) moderate wear (VB=0.235 mm); (c) severe wear (VB=0.483 mm)

Fig. 13 The DSS of tool 2 under different wear states (Workpiece material: 45# steel; speed 3000 rpm; feed: 1000 mm/min; cutting depth: 1 mm; cutting width: 4 mm): (a) sharp (VB=0 mm); (b) moderate worn tool (VB=0.235 mm); (c) severely worn tool (VB=0.483 mm)

Fig. 14 The trend of PSE value of tool 2 (Workpiece material: 45# steel; speed 3000 rpm; feed: 1000 mm/min; cutting depth: 1 mm; cutting width: 4 mm): (a) the vibration signal of the entire cutting process after removing the air cut part; (b) the result of PSE

Fig. 15 The trend of DSSE value of tool 2 (Workpiece material: 45# steel; speed 3000 rpm; feed: 1000 mm/min; cutting depth: 1 mm; cutting width: 4 mm): (a) the vibration signal of the entire cutting process after removing the air cut part; (b) the detection result of DSSE with threshold

The experiment results under cutting parameter 3 in Table 1 are shown in Figs. 16-20. The result is consistent with the aforementioned examples discussion. As can be seen from Fig. 20, the vibration amplitude is significantly larger from about the 130 minute to the 150 minute, and the DSSE has an obvious concave point at the 140 minute, which reveals the tool may be broken at here. The PSE value has also changed significantly at this stage. Tool breakage results in large vibration amplitude and great changes in DSSE. Fig. 21 shows the appearance of tool 3. It has been found that a small section is chipped off from the tip of tooth. The result of the experiment is in accordance with the theoretical prediction.

Fig. 16 The vibration signal of tool 3 under different wear states (Workpiece material: 45# steel; speed 1750 rpm; feed: 1050 mm/min; cutting depth: 0.7 mm; cutting width: 5 mm): (a) sharp (VB=0 mm); (b) moderate wear (VB=0.313 mm); (c) severe wear (VB=0.664 mm)

Fig. 17 The PS of tool 3 under different tool wear stages (Workpiece material: 45# steel; speed 1750 rpm; feed: 1050 mm/min; cutting depth: 0.7 mm; cutting width: 5 mm): (a) sharp (VB=0 mm); (b) moderate wear (VB=0.313 mm); (c) severe wear (VB=0.664 mm)

Fig. 18 The DSS of tool 3 under different wear states (Workpiece material: 45# steel; speed 1750 rpm; feed: 1050 mm/min; cutting depth: 0.7 mm; cutting width: 5 mm): (a) sharp ($VB=0$ mm); (b) moderate wear ($VB=0.313$ mm); (c) severe wear ($VB=0.664$ mm)

Fig. 19 The vibration signal and PSE value of tool 3 (Workpiece material: 45# steel; speed 1750 rpm; feed: 1050 mm/min; cutting depth: 0.7 mm; cutting width: 5 mm): (a) the vibration signal of the entire cutting process after removing the air cut part; (b) the result of PSE value

Fig. 20 The vibration signal and DSSE result of tool 3 (Workpiece material: 45# steel; speed: 1750 rpm; feed: 1050mm/min; cutting depth 0.7mm; cutting width 5 mm): **(a)** the vibration signal of the entire cutting process after removing the air cut part; **(b)** the detection result of DSSE with threshold

Fig. 21 The appearance of tool 3

The above research results show that the DSSE of cutting vibration signals decreases with tool wear development and has the same law under different cutting condition. The proposed method is an effective method for real-time monitoring tool wear and can accurately determine the degree of tool wear. As a conclusion, the method is simple and effective, and has good robustness.

5 Conclusions

This paper presents a method based on HOS entropy feature to monitor tool wear states. The DSS is the simplification of the bispectrum, which is more convenient than bispectrum in practical applications. Compared to PS, DSS has phase information, which is more advantageous in dealing with nonlinear and non-Gaussian systems. Moreover, the DSS can suppress the Gaussian noise. The DSS is used to distinguish different wear states of tool, and the DSSE is used to quantify the differences between them. The sharp tool has a high DSSE value and the worn tool has a low DSSE value. The DSSE decreases with tool wear development. By the obtained DSSE, a threshold method is designed based on the central limit theorem to explore tool wear severity estimation. At last, the experiment analyses

performed under varying cutting conditions verify the validity and the reliability of the proposed method. The research results demonstrate that the proposed method is an effective approach to monitor and diagnose the tool state. In conclusion, as tool wear indicator, the DSSE is not only immune to noise, but also can meet the actual needs of online monitoring, and has good potential for industrial application.

Declarations

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Availability of data and material

The datasets used in the study are available from the corresponding authors according to reasonable request.

Code availability

The code analyzed in the study are available from the corresponding author according to reasonable request.

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Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Authors' contributions

Bin Yang: Methodology, experimental design, data processing and analysis, writing-original draft preparation. Min Wang: Funding acquisition, project administration, supervision, review and editing article. Tao Zan: Providing lab facilities, experimental design. Xiangsheng Gao: Review and editing article. Peng Gao: Investigation, reviewing article.

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