The International Journal of Advanced Manufacturing Technology (2020) 111:2051–2063
https://doi.org/10.1007/s00170-020-06265-y

ORIGINAL ARTICLE

Milling chatter detection based on VMD and difference of power spectral entropy

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Received: 7 July 2020 / Accepted: 15 October 2020 / Published online: 22 October 2020

Abstract

Chatter is a kind of unstable vibration in high-speed milling process, leading to poor surface quality of workpiece, significant tool wear, and severe noise. In order to avoid these negative effects of milling chatter, the detection of chatter at early stage is highly needed. In this paper, an early-stage chatter detection method based on variational mode decomposition (VMD) and difference of power spectral entropy (ΔPSE) is presented. Considering that the existence of possible colored noise in the monitoring signals, which might lead to the misjudgment of chatter detection, the signals monitored at spindle's idling is utilized to identify these noise components. In order to separate the needed chatter-sensitive sub-signals, VMD is utilized to decompose the original signals into a series of intrinsic mode functions (IMFs), and the chatter-sensitive sub-signals are obtained by adding the IMFs whose central frequencies are closed to the milling system's natural frequency. After that, an adaptive filter is utilized to filter out the harmonics of spindle-speed frequency and the identified colored noise components. Then, a dimensionless indicator is designed, which is determined as the difference of power spectral entropy (ΔPSE) of signals without and with filtering. A series of experiments are also performed, and the results indicate that the presented methodology can detect the chatter at early stage and is applicable in different cutting conditions, which is very important in the practical application.

Keywords Milling chatter detection · Variational mode decomposition · Adaptive filter · Power spectral entropy

1 Introduction

Milling chatter is one type of self-excited vibration and causes some negative effects, such as poor surface finishes, unacceptable errors of workpiece, and machine tool's damage [1]. In order to avoid chatter, conservative cutting parameters such as lower cutting depth are usually selected with stability lobe diagram (SLD) in practical process [2]. However, a stable milling process is difficult to be guaranteed due to the nonlinear and time-varying behaviors of machining system, such as the change of machining dynamics caused by temperature, spindle speed, and tool wear, which might lead to the shift of SLD, and the selected stable cutting conditions might become unstable [3]. Therefore, the chatter detection and suppression have been important issues in the machining operations. In order to suppress or deal with the chatter vibration actively in machining, the chatter detection at early stage plays an important role and is highly needed.

Nowadays, different chatter detection methods haven been proposed by researchers. Overall, the chatter detection includes the signal acquisition, signal processing, and chatter indicator design. Due to the development of sensors, different kinds of signals have been utilized for chatter detection, such as cutting force signals [4–7], sound signals with acoustic emission [8–11], acceleration signal with accelerometer [12–16], and motor current [17, 18]. In addition, the machining surface images [19–22] are also utilized for the detection of chatter onset. In fact, the monitoring signal directly affect the performance of chatter detection, and the basic principle of chatter detection is based on the fact that different signal components or characteristics emerge in the signals when chatter happens, to hence a higher signal-to-noise ratio should be guaranteed. However, in practical application, the operating environments are quite complicated, and some colored noise component cannot be avoided, such as the significant noise caused by undesired

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vibration in machine tool and the operating vibration of needed auxiliary equipment (cooling system, gas seal and so on). With the existing methods of chatter detection, these significant noise components are easily detected as chatter components and should be carefully distinguished.

In order to obtain the chatter-sensitive signal component or exact the features that reflect the signals' fluctuation state, different signal processing methods have been presented. Due to the simplicity of calculation, time domain methods which extract one or more features are widely applied in chatter detection. Schmitz T L [3] calculated the variance of the synchronously sampled audio signal to identify the onset of chatter in milling. Van et al. [23] modeled the monitoring signal with autoregressive moving average model and identify the milling chatter by judging the model's feature root. Ye et al. [24] calculated the root mean square sequence of the monitoring acceleration signal, and determined the ratio of the standard deviation and the mean of the root mean square sequence as indicator for chatter detection. Though the time domain method is simple, misjudgment easily happen when some sudden shock occurs and the threshold of selected indicator is difficult to determine. Frequency domain methods are also utilized to extract the features related to chatter components from the signal in frequency domain. For example, Liao [4] used fast Fourier transformation (FFT) to analyze the filtered cutting force signals and identify the chatter frequency components. However, due to the fact that the monitoring signal is non-stationary during the development of chatter, hence the traditional frequency domain method is not suitable.

Considering that the monitoring signal is non-stationary when the cutting state shifts from stable to chatter, the time-frequency methods have been widely utilized in recent years to track the instantaneous state of machining operation. Wavelet packet decomposition (WPD) is one of the time-frequency methods utilized for the chatter detection in the past few years [25–27] and shows an excellent performance. However, the high-frequency resolution of WPD is poor, and the wavelet base functions and number of layers of WPD should be carefully selected. Empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD) are also widely used in chatter detection [15, 28, 29]. Liu et al. [29] proposed a chatter identification methods by combining EMD and WPD, and the mode mixing problem is solved with WPD. Shrivastava et al. [28] utilized EMD to identify the most dominating mode which is pertaining to chatter, and a statistical indicator was designed as the chatter indicator. Due to the possible mode mixing problem, ensemble empirical mode decomposition (EEMD) method is developed and also applied to the chatter detection. Ji et al. [15] proposed a milling chatter detection method based on EEMD. Wan et al. [30] utilized EEMD to identify the dominating chatter frequency when chatter is detected. In addition, the variational mode decomposition (VMD) method developed by Dragomiretskiy et al. [31], which takes advantage of adaptive, quasi-orthogonal, non-recursive decomposition, has also been widely utilized in different aspects. Liu et al. [32] presented a milling chatter detection method based on VMD and the energy entropy was determined as the indicator of chatter. Yang [33] utilized VMD to develop a reliable, real-time chatter detection method, in which the parameters of VMD are optimized.

In summary, different chatter detection methods have been proposed extensively. However, some deficiencies still exist in terms of the dependence on signal's quality, the applicable performance in different cutting conditions. Though the signal quality can be guaranteed in most conditions, some colored noise components still might exist in the monitoring signal, which mainly come from operating environment of machine tool and some complicated vibration caused by the machine tool's dynamics, and these components easily lead trouble to the chatter detection when they cannot be neglected. In addition, in the above-mentioned chatter detection methods, a popper threshold should be given and the threshold might not work in different cutting conditions, due to the fact that the designed indicators are directly or indirectly related to the cutting conditions. Hence, a proper indicator, whose physical meaning is independent on the actual cutting conditions, is highly needed, which means the amplitude or the sudden shock of monitoring signal do not affect the designed indicator.

In this study, a milling chatter detection methodology based on VMD and difference of power spectral entropy is presented. Considering that the existence of possible colored noise in the monitoring signal easily leads to the misjudgment of chatter, the signals at spindle's idling are utilized to identify these noise components. In order to separate the needed chatter-sensitive sub-signals, VMD is utilized to decompose the original signal into a series of intrinsic mode functions (IMFs), and the chatter-sensitive sub signals are obtained by adding the IMFs whose central frequencies are closed to the milling system's natural frequency. After that, the adaptive filter is utilized to filter out the harmonics of spindle-speed frequency and identified colored noise components. Then, a dimensionless indicator is designed, which is determined as the difference of power spectral entropy (ΔPSE) of signals without and with filtering. A series of experiments are also performed, and the results show that the presented methodology can detect the chatter well and is applicable in different cutting conditions.

The rest of this paper is organized as follows. Section 2 analyzes the components of monitoring signal at different cutting states in milling. In Section 3, the proposed methodology is presented based on the signal's characteristics discussed in Section 2. More milling experiments under different cutting conditions are performed, and the results are shown in Section 4. Conclusions are drawn in Section 5.

2 Signal component analysis for chatter detection

Nowadays, different types of monitoring signals have been utilized to detect the onset of chatter vibration in machining, like vibration signals, sound signals, and force signals [34]. Kuljanic et al. [35] compared different sensors for chatter detection in milling process and found that the vibration signals obtained with accelerometer showed better performance. Though the selected sensor plays an important role in chatter monitoring, the signal quality directly determines the performance of chatter detection. In this section, milling experiments are performed to obtain the monitoring signals from stable to chatter, and then the components of monitoring signals for chatter detection are analyzed.

Figure 1 shows the experimental setup for milling experiments, a 3-axis milling machine is utilized, and an accelerometer (B&K4525) is attached to the spindle to monitor the vibration during milling operations, and the signals are recorded with a B&K data acquisition (DAQ). During the milling experiments, an end mill cutter with two flutes, diameter 4 mm, and overhang 30 mm is used. In order to obtain the vibration signals at different stages, a wedge-shaped workpiece shown in Fig. 2 is selected, and then the axial cutting depth shifts from 0 to 8 mm with a cutting length of 100 mm. The other cutting parameters are spindle speed 4800 rpm, radial cutting depth 1 mm, and feed rate 90 mm/min, and sampling frequency is 4096 Hz. Before the cutting experiments, the natural frequencies of milling system in each direction are also identified with impact test at the tool tip position, and the results are listed in Table 1.

The milling experiment results are shown in Fig. 3. Figure 3a presents the recorded vibration signals, and it can be found that the amplitude of vibration increases slowly with a higher cutting depth and an obvious fluctuation occurs in some stages of the signals. In order to analyze the characteristics of monitoring signals, the spectrum of signals at different stages are also shown in Fig. 3b–d. Figure 3b illustrates the comparison

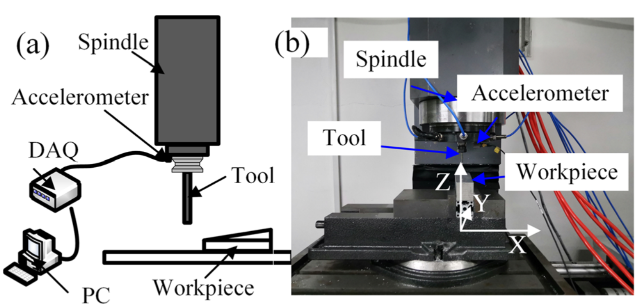

Fig. 1 Experimental setup: **a** schematic diagram and **b** photo of the experimental setup

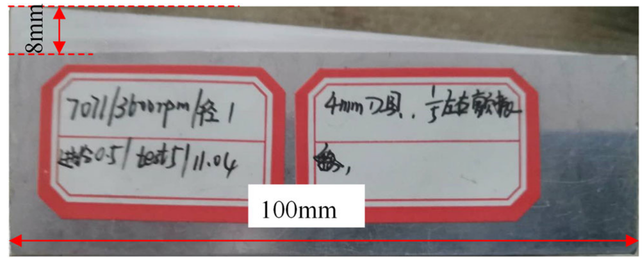

Fig. 2 Wedge-shaped workpiece for milling experiments

between the signals at stage A and stage B, and it can be found that the harmonics of rotating frequency are the main components in the signals, which are mainly caused by the unbalance of spindle system, cutting excitation, and possible misalignment between the stator and rotor of installed motor. Meanwhile, some other weak signal components (with frequency 1080 Hz, 1151 Hz, 1566 Hz, 1639 Hz and 1708 Hz) exist in stages A and B. With traditional chatter detection, these weak components (different with harmonics) are easily detected as the onset of chatter during the milling. However, due to the fact that these components also exist in stage A (with spindle idling and no cutting), these components are actually colored noise components in the monitoring signals, and no chatter occurs in stage B. In fact, the noise always exists in the machining process, such as the cooling system for spindle, gas seal of the spindle system, and other complicated vibrations in the machine tool. Usually, these noise components can be neglected when they are weak enough. However, these colored noise components might easily lead to misjudgment for the chatter detection when these noise components are notable in the monitoring signals. Fig. 3c shows the spectrum of monitoring signal at early stage of chatter (stage C), where weak chatter components emerge and the mentioned noise components still exist. When the chatter is fully developed, as shown in Fig. 3d, the chatter components become more obvious. Hence, it is desired to detect the occurrence of chatter at an early stage, where the chatter components begin to emerge in the monitoring signal. By analyzing the distribution of chatter components in Fig. 3c and d, it can also be found that the chatter frequencies are distributed around the natural frequencies of spindle system, which is consistent with the results claimed by Altintas [2].

Table 1 Identified natural frequency of milling system

Direction	1st natural frequency (Hz)	2nd natural frequency (Hz)
X	980	1424
Y	980	1409

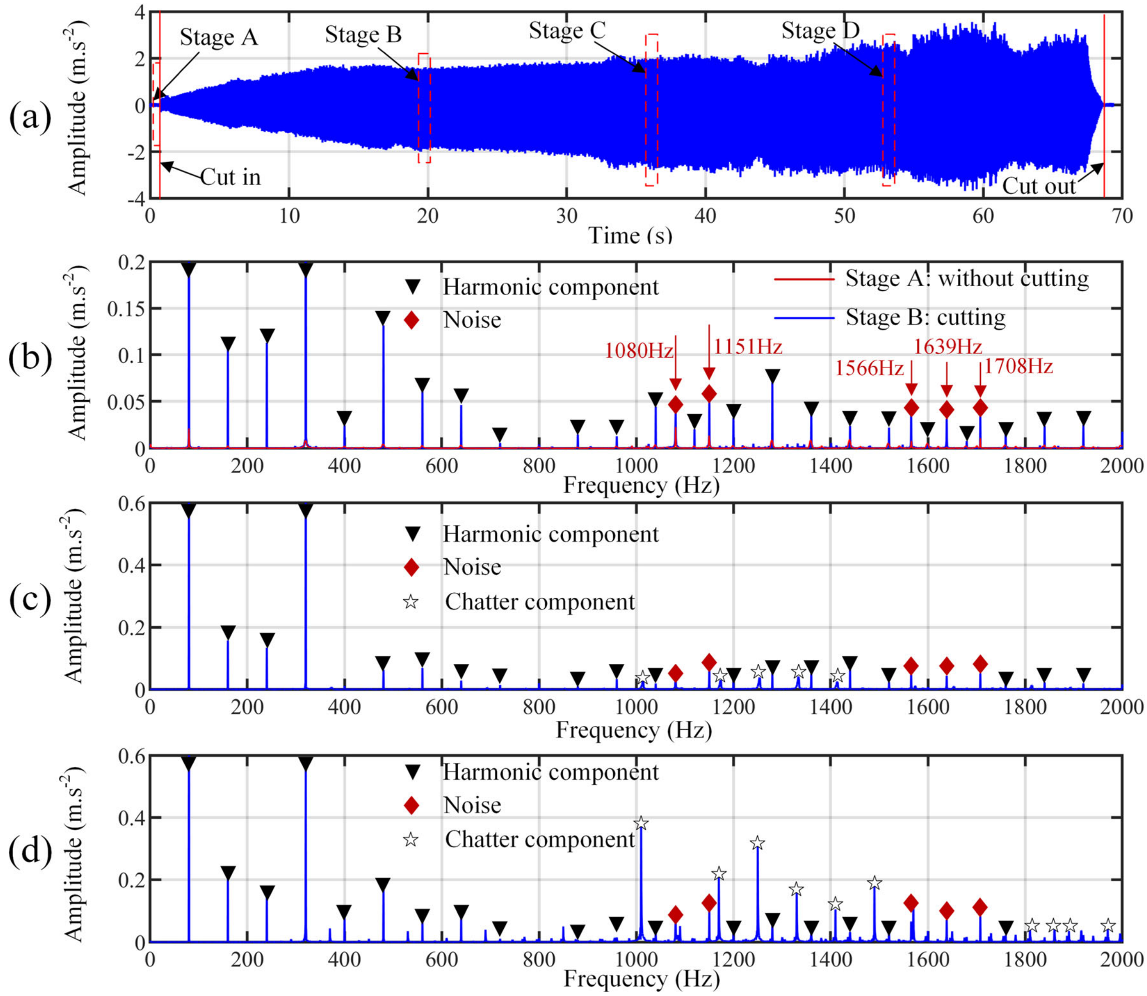

Fig. 3 Signal component analysis for chatter detection: **a** monitoring signals in time domain, **b** comparison of signal's spectrum at stages A and B, **c** spectrum of signals at stage C, and **d** spectrum of signals at stage D

3 Methodology

3.1 Noise component identification

Through the signal component analysis in Section 2, the noise component in the monitoring signals easily disturbs the chatter detection in practical application and should be identified and filtered out. Hence, the method of adaptive identification of noise components in the signals is presented firstly. Due to the fact that noise components keep constant at different cutting stages, it is intended to identify these components adaptively with the monitoring signal when the spindle is idling (without cutting).

Assume $\mathbf{S}_0 = [s_0(1), s_0(2), \cdots, s_0(N)]$ is the obtained signals with length N before the tool cut in, and the corresponding Fourier transformation is the following

$$F(i) = \frac{1}{N}\sum_{l=1}^{N} s_l exp\left(\frac{2\sqrt{-1}\pi}{N}\right)^{-l \cdot i}, i = 1, 2, \ldots, N \tag{1}$$

and the root mean square value of $F(i)$ is

$$G = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |F(i)|^2} \tag{2}$$

Similar with 3σ criterion in [36], the spectrum components that satisfy $|F(i)| \geq rG$ are identified as noise components here, and $r = 9$ is utilized in this paper. Then the corresponding frequency of noise components can be identified as

$$f_0 = \frac{f_s}{N} \cdot i \tag{3}$$

where f_s is the sampling frequency.

When the first noise component is identified, reset the corresponding Fourier transformation value as 0, and repeat the above process until all the obvious noise components are identified, and the flowchart is shown in Fig. 4. Then, a series of noise components can be identified adaptively, with the frequency series $\mathbf{f}_0 = [f_{0,1},$

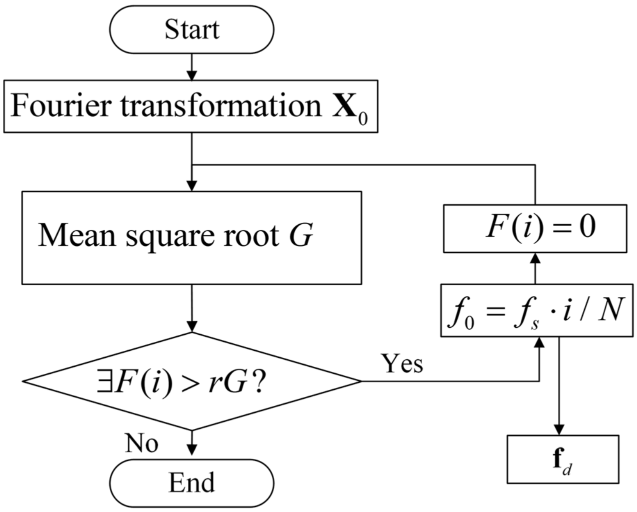

Fig. 4 Flowchart of noise components identification

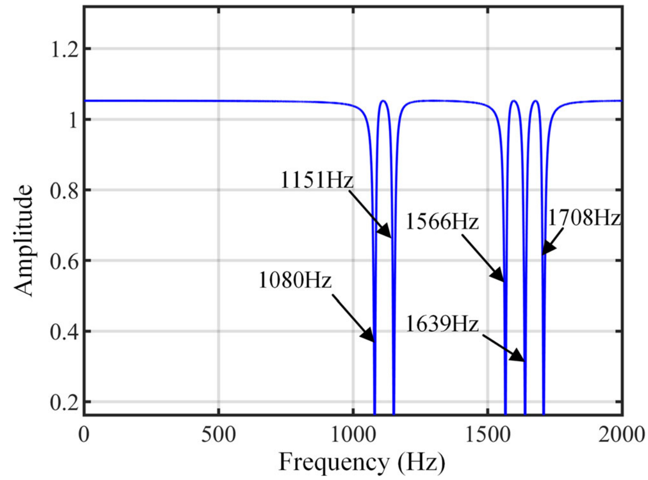

Fig. 6 Spectrum of designed adaptive filter to move out the noise components (shown in Fig. 3)

$f_{0,2}, \cdots]$. It should be noted that the harmonics of spindle speed frequency can also be identified with the above process. In practical application, the harmonics can also be determined with the information of spindle speed.

3.2 Separation of chatter-sensitive band signal with VMD

As analyzed in Section 2, when chatter occurs, the chatter components usually distribute around the natural frequency of spindle system. Hence, it is desired to separate the chatter-sensitive sub-signals from the original monitoring signals. Nowadays, different methods have been utilized to decompose the signals into a series of sub-signals with various bands, such as WPD [37, 38] and EMD/EEMD [25, 39]. In this section, considering that the VMD takes the advantages of small endpoint effect and less mode mixing, the VMD method is utilized to decompose the original monitoring signals and separate the needed chatter-sensitive sub-signals for the chatter detection.

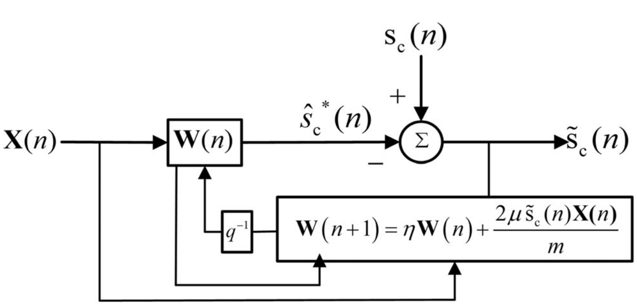

Fig. 5 Structure of adaptive filter

In VMD [22], assume that the signals are decomposed to a series of intrinsic mode functions (IMFs) with number K and each IMFs can be defined as a series of amplitude-modulation and frequency-modulation signals, which are expressed as

$$u_k(t) = A_k(t)\cos(\varphi_k(t)), k = 1, 2, \ldots, K \tag{4}$$

where $A_k(t)$ is the instantaneous amplitude and $\omega_k(t) = \varphi'_k(t)$ is the corresponding instantaneous frequency. For an original signal segment $x(t)$, the VMD process is a constrained optimization problem:

$$\left\{ \min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\sigma(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \text{ s.t. } \sum_{k=1}^{K} \mathbf{u}_k = x(t) \right. \tag{5}$$

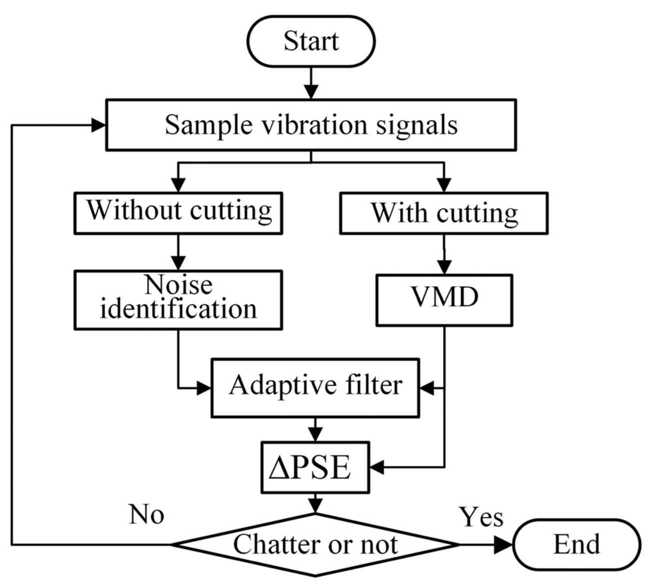

Fig. 7 Flowchart of developed chatter detection method

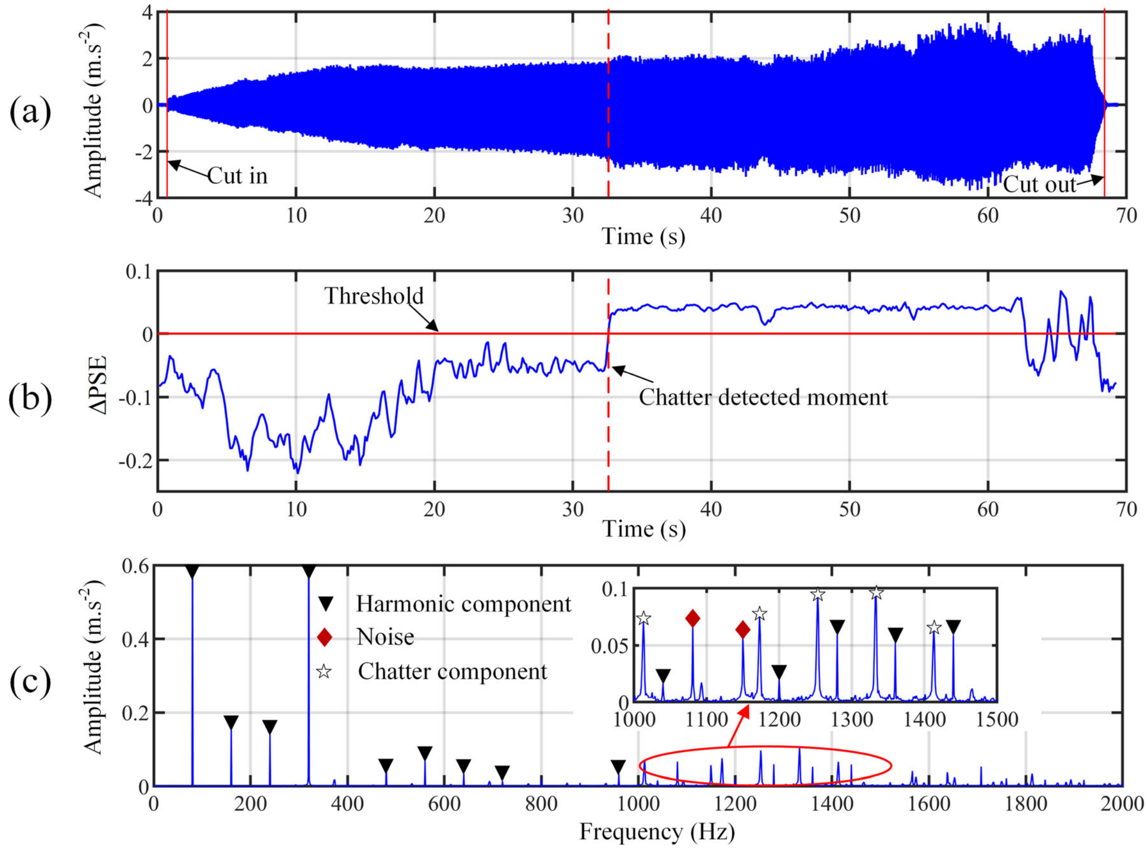

Fig. 8 Chatter detection result: **a** signals in time domain, **b** indicator of ΔPSE, and **c** spectrum of signal at chatter detected moment

By introducing penalty term α and Lagrange multiplier λ, an augmented Lagrange function is obtained:

$$\begin{aligned} \mathrm{L}(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\sigma(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| x(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 \\ + \left[\lambda(t) \cdot \left(x(t) - \sum_{k=1}^{K} u_k(t) \right) \right] \end{aligned} \quad (6)$$

So the problem described in Eq. (5) is transformed into an unconstrained problem (Eq. (6)). During the iterative solution process, the bandwidth and center frequency of the IMFs are continuously updated, and finally a series of narrow-band IMFs are obtained.

With VMD, the signal segment $\mathbf{S} = [s(1), s(2), \cdots, s(N)]$ with length N can be decomposed to a series of narrow-band IMFs $\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_K$, and the corresponding central frequencies are$\omega_1\ \omega_2\ \ldots\ \omega_K$, respectively. In order to obtain the chatter-sensitive sub-signals, these decomposed IMFs with a center frequency near the milling system's natural frequency are accumulated as new signals:

$$\mathbf{S}_c = \sum \mathbf{u}_{k,c} \quad (7)$$

where $\mathbf{u}_{k,\ c}$ is the IMFs whose central frequency is in the frequency band (ω_l, ω_h) andω_l and ω_h denote the upper and down of concerned frequency band, respectively, and can be determined by considering the distribution of milling system's natural frequency.

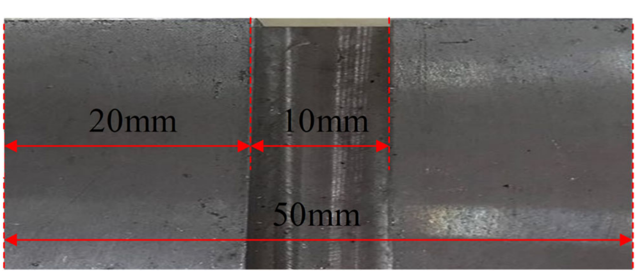

Fig. 9 Grooved workpiece

3.3 Signal filtering with adaptive filter

Though the chatter-sensitive sub-signals with VMD is intended to improve the performance of chatter detection, the harmonics of spindle speed frequency and noise components discussed in Section 3.1 still affect the early-stage chatter detection, due to the fact that the chatter components at early stage are easily submerged by these undesired signal components.

In order to move out these harmonics and noise components, an adaptive filter is utilized to filter out these components, with the structure shown in Fig. 5. $s(n)$ is the input of adaptive filter and denotes the nth time series in the original signal segment $\mathbf{S}_c = [s(1), s(2), \cdots,]$. $\mathbf{X}(n)$ and $\widetilde{s}_c(n)$ are called

Table 2 Parameters of experiments with different cutting conditions

No. of test	Wokpiece	Cutting parameters				
		Material	Spindle speed (rpm)	Feed speed ($mm \cdot min^{-1}$)	Axial depth (mm)	Radial depth (mm)
1	#1	7075	3600	30	0–8	1
2	#1	6061	4800	30	0–8	1
3	#1	7075	5400	90	0–8	1
4	#2	6061	4800	90	1	1
5	#2	7075	4800	90	3	1

the reference input and reference output of adaptive filter, respectively. Here, the reference input $\mathbf{X}(n)$ takes the following forms:

$$\mathbf{X}(n) = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_m]^T \tag{8}$$

where m denotes the number of frequency components that needed to be filtered out and each element of $\mathbf{X}(n)$ is expressed as:

$$\mathbf{x}_i = [\cos(2\pi f_i \cdot nT_s), \sin(2\pi f_i \cdot nT_s)] \tag{9}$$

where f_i denotes the ith frequency component and T_s is the sampling time interval.

Through the adaptive filter theory [40], the estimation of signal components that needed to be filtered out can be defined as:

$$\widehat{s}_c^{\ *}(n) = \mathbf{W}(n) \cdot \mathbf{X}(n) \tag{10}$$

where $\mathbf{W}(n)$ denotes the weight vector. According to the principle of signal superposition, the difference between $s_c(n)$ and $\widehat{s}_c^{\ *}(n)$ becomes the desired signal for chatter detection, when the signal components that needed to be filtered out ($\widehat{s}_c^{\ *}(n)$) are well estimated. In order to obtain the optimal estimation of $\widehat{s}_c^{\ *}(n)$, least mean square (LMS) algorithm is utilized to

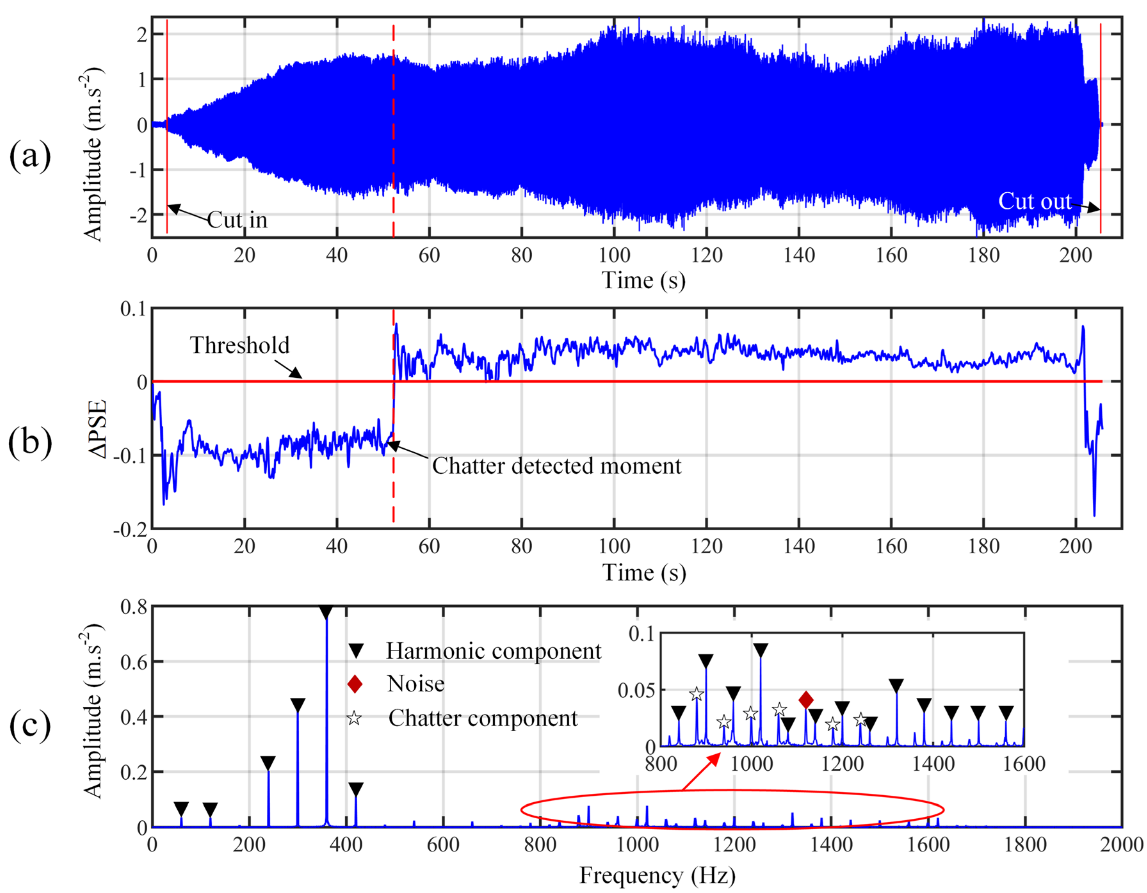

Fig. 10 Experiment result of test 1: **a** signals in time domain, **b** indicator of ΔPSE, and **c** spectrum of signal at chatter detected moment

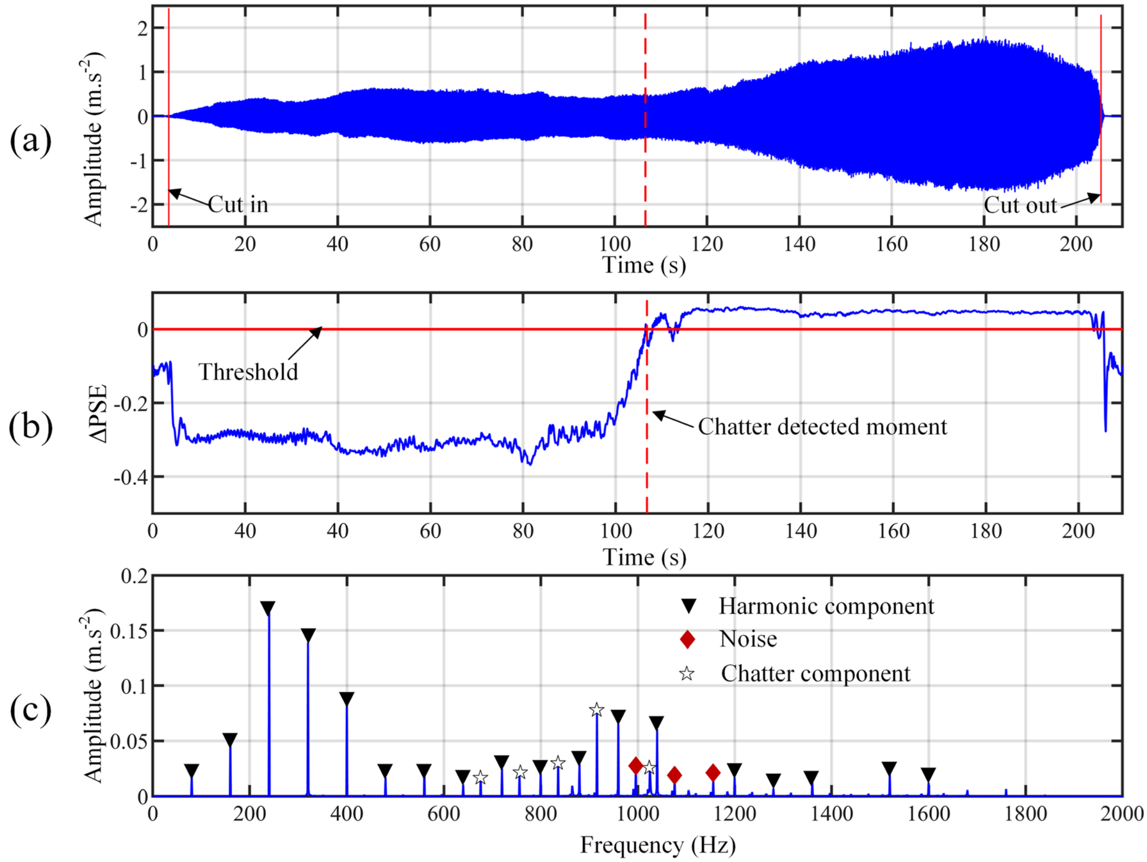

Fig. 11 Experiment results of test 2: **a** signals in time domain, **b** indicator of ΔPSE, and **c** spectrum of signal at chatter detected moment

update the weight vector $\mathbf{W}(n)$, with the following expression:

$$\mathbf{W}(n+1) = \eta \mathbf{W}(n) + \frac{2\mu \widetilde{s}_{\mathrm{c}}(n)\mathbf{X}(n)}{m} \tag{11}$$

where η and μ denote the forgetting factor and step size, respectively. In Fig. 5, q^{-1} denotes the shift operator, with $\mathbf{W}(n) = q^{-1}\mathbf{W}(n+1)$.

Figure 6 shows the proposed filter used to filter out the identified noise components in Section 2. Obviously, it can be found that the noise components can be well filtered with the proposed filter. It should be noted that the harmonics of spindle speed frequency components are also filtered out with the presented adaptive filter by resetting the f_i in Eq. (9), as presented in the author's previous work [41].

3.4 Indicator design for chatter detection

In milling chatter detection, one or more features which reflect the milling state are usually extracted as indicators to distinguish the onset of chatter. Considering that the distribution state of different frequency components in the signals can be evaluated with the entropy, hence a specific indicator based on the signal's power spectral entropy is designed in this paper.

For the signal segment $\mathbf{S}_{\mathrm{c}} = [s_{\mathrm{c}}(1), s_{\mathrm{c}}(2), \cdots, s_{\mathrm{c}}(N)]$ with length N, the corresponding power spectrum can be presented with:

$$P_S(\omega_i) = \frac{1}{2\pi N} |S(\omega_i)|^2 \tag{12}$$

where $S(\omega_i)$ is the ith FFT series of signal segment $\mathbf{S}_{\mathrm{c}}$ and ω_i denotes the ith corresponding frequency series.

The probability density function for the unilateral power spectrum power spectrum $P_S(\omega_i)$ takes the following expression:

$$P_i = \frac{P_S(\omega_i)}{\sum_{i=1}^{\left\lfloor \frac{N}{2} \right\rfloor} P_S(\omega_i)} \quad , i = 1, 2, \ldots, \left\lfloor \frac{N}{2} \right\rfloor \tag{13}$$

where $\left\lfloor \frac{N}{2} \right\rfloor$ means round down and P_i is the probability density of $P_S(\omega_i)$.

Next, the power spectral entropy of signal segment $\mathbf{S}_{\mathrm{c}}$ can be calculated and normalized by:

$$H = \frac{-\sum_{i=1}^{\left\lfloor \frac{N}{2} \right\rfloor} P_i \cdot \ln(P_i + \delta)}{\ln \left\lfloor \frac{N}{2} \right\rfloor} \tag{14}$$

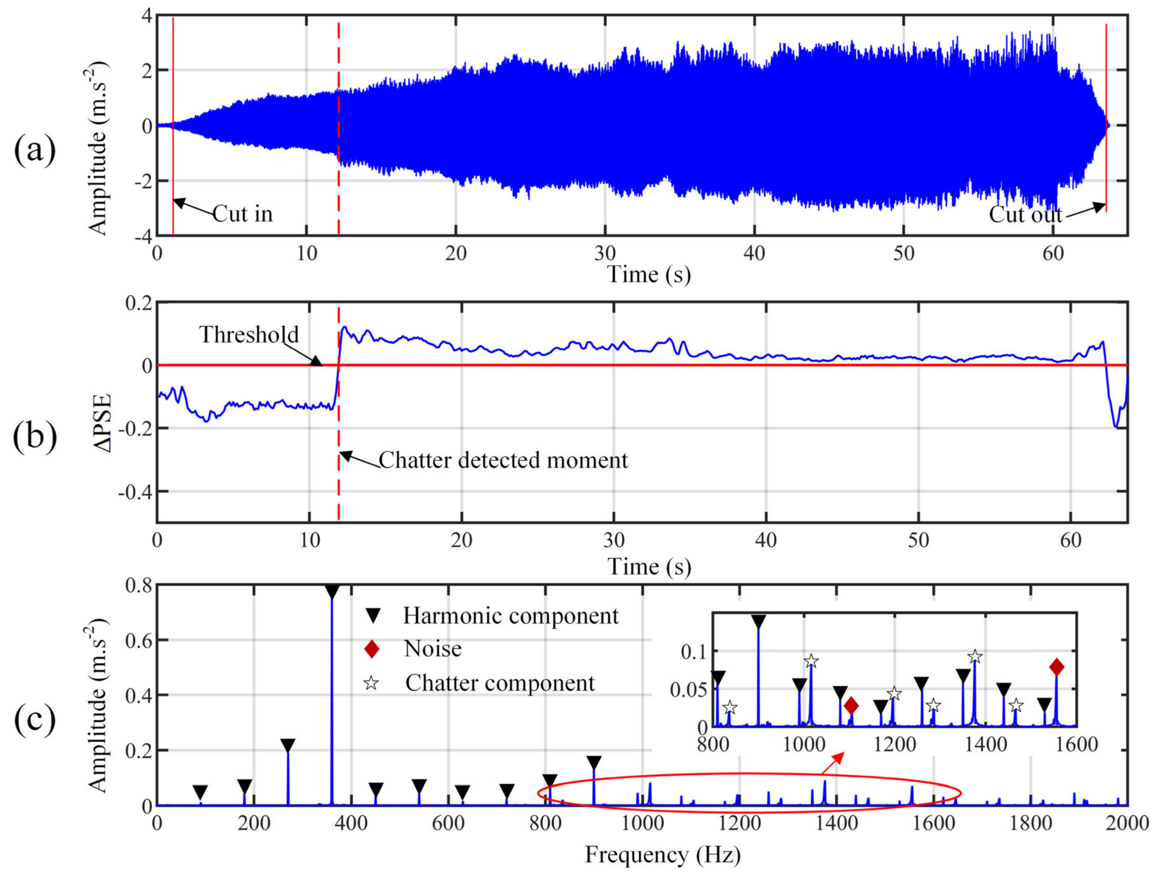

Fig. 12 Experiment results of test 3: **a** signals in time domain, **b** indicator of ΔPSE, and **c** spectrum of signal at chatter detected moment

where δ is a very small positive constant, which is used to avoid the situation that P_i equals zero, and $\delta = 0.001$ is selected.

Hence the difference of power spectral entropy of signals without and with filtering is designed as indicator of chatter detection, with the following expression:

$$\Delta \mathrm{PSE} = H - \widetilde{H} \tag{15}$$

where $\widetilde{H}$ denotes the power spectral entropy of filtered signal in Section 3.3.

The indicator ΔPSE reflects the trend of monitoring signal during chatter detection process. Through the signal's characteristics discussed in Section 2, when the cutting state is stable, there are mainly harmonics, possible colored noise components and white noise in the monitoring signal segment, and only white noise exists when the signal is filtered with the designed adaptive filter in Section 3.3. Compared with the signal without filtering, the distribution of signal, whose harmonic and possible colored components have been filtered out, becomes more uniform, which means $\widetilde{H}$ is absolutely larger than H and hence $\Delta\mathrm{PSE} < 0$. However, when chatter occurs and the cutting state becomes unstable, chatter components exist in the filtered signals and concentrated to a band related to the milling system's natural frequency, and compared with the filtered signals, the original signals without filtering are more uniform (as shown in Fig. 3c). Hence, the power spectral entropy of signal without filtering is larger than the filtered signals' power spectral entropy and $\Delta\mathrm{PSE} > 0$. With the above analysis, $\Delta\mathrm{PSE} = 0$ is inteded to be a reasonable threshold for chatter detection.

3.5 Workflow of developed chatter detection method

Figure 7 shows the final flowchart of developed chatter detection method in this paper. The monitoring signals in Section 2 are utilized here to evaluate the performance of the proposed method, and more experiments are performed in the next section.

Figure 8 shows the results of chatter detection with the monitoring signals in Section 2. During the chatter detection process, each segment of the signal has a length of 512 sample points. Through the results shown in Fig. 8b, it can be found that the chatter is detected at about 32.6 s with the proposed methodology. Weak chatter components also can be found with the spectrum of signal when chatter is detected (shown in Fig. 8c), which means the chatter can well be detected with the presented method.

4 Experiments and discussion

For the chatter detection, it is desired to be applicable under different cutting conditions, especially the designed indicator and selected threshold. Hence, in this section more experiments under different cutting conditions are performed to verify the performance of chatter detection with proposed methodology in this paper. During the experiments, different materials of workpiece, spindle speed, feed rate, cutting depth, are selected. In addition to the wedge-shape workpiece shown in Fig. 2, a grooved workpiece with depth 5 mm is also utilized (shown in Fig. 9). For the convenience of expression, #1 and #2 are utilized to denote the wedge-shape workpiece and grooved workpiece, respectively. All the experiments are performed on the experimental setup introduced in Section 2, and the parameters of experiments with different cutting conditions are listed in Table 2.

Figure 10 shows the result of test 1. The signals in time domain are shown in Fig. 10a, and Fig. 10b is the ΔPSE indicator for chatter detection. It can be found that the chatter is detected at 52.5 s with the proposed methodology. The spectrum of the signal section between 52 and 53 s is shown in Fig. 10c, and there are chatter components in 800–1400 Hz, which means the chatter exactly occurs.

Figure 11 shows the result of test 2. The signals in time domain are shown in Fig. 11a, and Fig. 11b is the ΔPSE indicator for chatter detection. It can be found that the chatter is detected at 106.6 s with the proposed methodology. The spectrum of the signal section at chatter detected moment (shown in Fig. 11c), and there are chatter components in 800–1000 Hz, which means the chatter occurs exactly.

Figure 12 shows the result of test 3. The signals in time domain are shown in Fig. 12a, and Fig. 11b is the ΔPSE indicator for chatter detection. It can be found that the chatter is detected at 12 s with the proposed methodology. The spectrum of the signal at chatter detected moment is shown in Fig. 12c, and there are chatter components in 800–1600Hz, which means the chatter occurs exactly.

The results of tests 1–3 prove that the proposed methodology with a threshold ΔPSE = 0 can detect chatter quickly and accurately under different cutting conditions. In these experiments, wedged workpiece is utilized, and the axial cutting depth increases from 0 mm, and no significant shock occurs. When the workpiece is a grooved workpiece, there is an instantaneous shock at the moment of cut in, leading challenges of avoiding misjudgment in chatter detection.

Figure 13 shows the result of test 4, the signals in time domain are presented in Fig. 13a. During 0–1.3 s and 15.4–

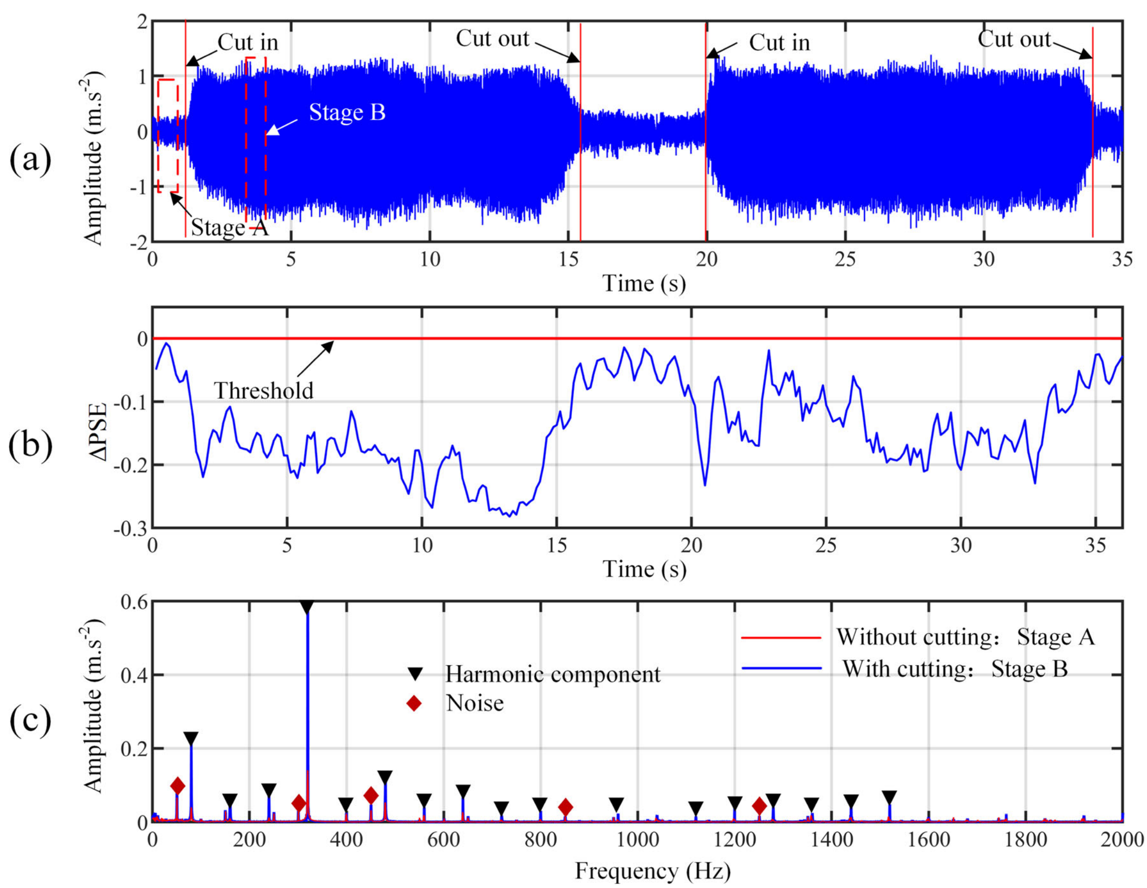

Fig. 13 Experiment results of test 4: (a**)** signals in time domain, (**b**) indicator of ΔPSE, and (c) spectrum of signal with and without cutting

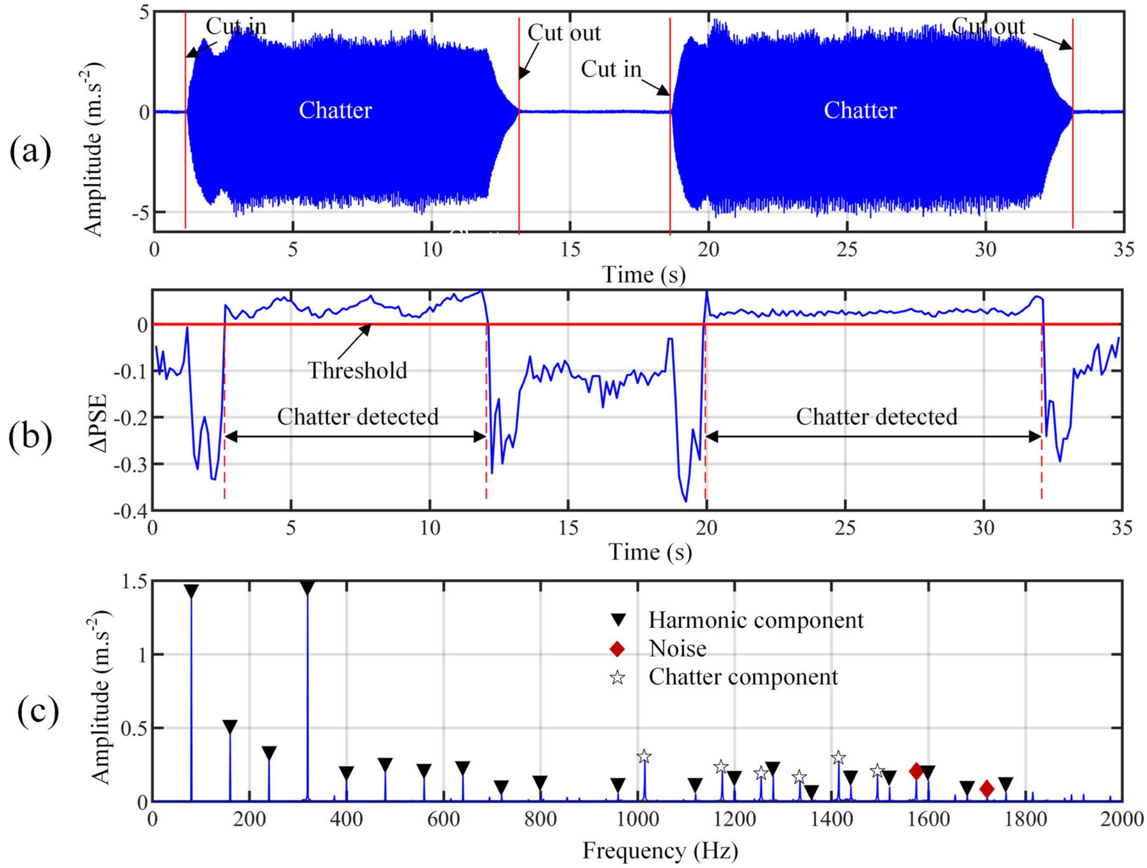

Fig. 14 Experiment results of test 5: **a** signals in time domain, **b** indicator of ΔPSE, and **c** spectrum of signal when chatter is detected

19.9 s, the spindle system is running without cutting, and the amplitude is small. Figure 13b is the ΔPSE indicator extracted through the proposed methodology, and no chatter is detected. Figure 13c illustrates the spectrum of signals without and with cutting, and it can be found that no chatter components emerge apart from the colored noise components in the monitoring signals, which means no chatter occurs exactly. In addition, though significant shock happens when the tool cut in and cut out, in which moment that chatter might be easily misdetected, the presented method still performs well.

Figure 14 shows the result of test 5, and the signals in time domain are shown in Fig. 14a. During 0–1.2 s and 13.2–18.8 s, the spindle system is running without milling. Figure 14b is the ΔPSE indicator extracted through the proposed methodology, and chatter is detected during the cutting process. In order to verify whether chatter occurs, Fig. 14c illustrates the spectrum of signals during the cutting, and it can be found that chatter components emerge apart from the colored noise components in the monitoring signals, which means chatter occurs exactly.

The results of tests 4–5 prove that the proposed methodology with a threshold $\Delta PSE = 0$ is also applicable in the common cutting conditions, where sudden shock exists due to the change of cutting depth, cutting in, and cutting out process, and the possible misjudgment of chatter detection can be avoided.

5 Conclusion

This paper proposes a new methodology for milling chatter detection at early stage. Through the characteristic analysis of monitoring signals, it can be found that some colored noise components possibly exist, due to the vibration of cooling system, gas seal, and some complicated vibrations in machine tool, and these noise components are easily detected as chatter with the existing methods. Considering that these noise components always exist during the machining operation, the monitoring signals at spindle's idling state are utilized to identify the frequency of noise components. When chatter occurs, the chatter components usually distribute in the band around the milling system's natural frequency; hence, the monitoring signals are decomposed into a series of IMFs, and the chatter-sensitive sub-signals are obtained by adding the IMFs whose central frequency locates in the chatter-sensitive band. Due to the fact that weak chatter components are usually submerged by the harmonics of spindle speed frequency and identified noise components at early stage of chatter, adaptive filter is designed to filter out the harmonics and noise components. After that, the difference of power spectral entropy of the signal without and with filtering (ΔPSE) is calculated as the indicator for the onset of chatter, and a very simple threshold $\Delta\text{PSE} = 0$ is utilized. A series of milling experiments under different cutting conditions are performed, and the results show that the proposed method and determined threshold perform well in different cutting conditions, which is beneficial for the practical application. The presented methodology can also be applied in the chatter detection in turning or grinding in the future.

Funding This work was supported by the National Key Research and Development Program of China (No. 2018YFB2000504) and Major technology projects of in Shaanxi province of China (No. 2018zdzx01-02-01) and Fundamental Research Funds for the Central Universities and National Science (No. xzd012019032). The authors express their gratitude for their support.

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