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ORIGINAL ARTICLE

A novel approach for chatter online monitoring using coefficient of variation in machining process

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Abstract
Chatter is one form of severe self-excited vibration in machining process which leads to many machining problems. In this paper, a new method of chatter identification is proposed. During the machining process, the acceleration signal of vibration is obtained and the time domain root mean square value of the acceleration is calculated every proper segment, through which the real-time acceleration root mean square (RMS) sequence is obtained. Then, the coefficient of variation (i.e., the ratio of the standard deviation to the mean, CV) of the RMS sequence is defined as the indicator for chatter identification. The milling experiment shows that CV can well distinguish the state (stable or chatter) of the machining process. The proposed method has a quantitative and dimensionless indicator, which works for different machining materials and machining parameters, and even can be expected to work in a wider range condition, such as different machine tool and cutting method. This paper also designs a fast algorithm of CV, making it an ideal candidate for online monitoring system.

Keywords Chatter · Online monitoring · Coefficient of variation

1 Introduction

Chatter is a severe self-excited vibration in machining process which puts the cutting system in an unstable state, leading to lower machining accuracy and surface quality, hash noise, and shorter tool life [1]. A great deal of effort has been dedicated to model the cutting system, including the work of Altintas [1], Budak [2], Tlusty [3], etc. However, due to the complexity and time-varying characteristic of the cutting system, analytic method still could not precisely model the actual machining process and prevent the occurrence of chatter [1]. Therefore, online cutting state monitoring and chatter detection is essential to maintain machining stability and quality in practical machining process.

Extensive studies on chatter detection have been carried out in recent years and the result is fruitful [4–8]. Most studies follow three steps: acquire signal, information extraction, and propose chatter indicator.

Commonly used signals in chatter monitoring include cutting force [9–13], acceleration [14–20], sound [21, 22], surface topography [12, 13, 23], and motor current [24, 25]. Regardless of the signal, the key of the analysis is utilizing proper signal processing technique to extract information from the signal. Signal processing methods can be roughly divided into three categories: time domain method [11, 26], frequency domain method [12, 27–29], and time-frequency analysis [10, 16, 18, 20, 22, 30, 31]. Because the time-frequency analysis, including STFT, wavelet analysis, and Hilbert-Huang transform, can simultaneously utilize time and frequency domain information of the signal, it has been the focus of research in recent years. Among them, the Hilbert-Huang transform [9, 10, 16, 17, 31] is widely used in chatter monitoring research because of its adaptive characteristics to non-stationary signals.

The choice of chatter indicator varies. The most common practice is setting the extracted information as the chatter indicator [10, 16, 28, 30, 31]. Some studies use pattern recognition method to perform the final judgment, such as logistic regression [20], support vector machines [24], hidden Markov model [15], and neural networks [19, 32]. To make the system more robust, some scholars use multi-signal analysis [12, 29,

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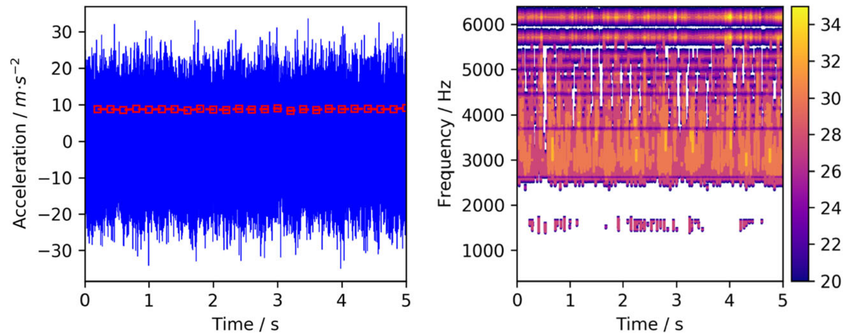


Fig. 1 Al-5a06, spindle speed = 9000 rpm, cutting depth = 1.7 mm, stable. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 20 do not show in figure

33] to construct comprehensive indicators, improving the reliability of identification. Also, some focus on only one type of machining, such as turning long slender workpiece [34]. And the idea of sensor-less chatter detection [35] is very intriguing.

Time-frequency analysis method is computationally expensive, and the methods based on pattern recognition usually require a large training samples and a long training time. To apply these chatter monitoring algorithms in practice, quantification and applicable range of the chatter indicators need to be improved. This paper presents a new method to identify chatter which has the advantages of wide application range, quantitative parameter, and low computation complexity. This paper also proposed a fast algorithm for online chatter monitoring.

2 Methodology

2.1 RMS sequence

First, the original vibration acceleration data needs to be pretreated, and the pretreatment should meet the flowing criteria:

After treatment, the data set must reveal the fluctuation, if any, of the original data;

It is preferable that the pretreatment can downsize the original data, which makes it much easier to implement the algorithm into an online monitoring system.

The RMS sequence, which is obtained by calculating the root mean square value of the vibration acceleration signal every N data points, meets both criteria. The dynamic change of the signal amplitude can be expressed by this sequence, and the data size is down to $1/N$ of the original.

$$a_{\mathrm{RMS}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {a_i}^2} \tag{1}$$

Example accelerations, their RMS sequences, and the corresponding time-frequency distributions are shown in Figs. 1, 2, 3, 4, 5, 6, 7, and 8. The time-frequency distribution is obtained by continuous wavelet transformation, using Morlet wavelet. To display the variance clearly, coefficients less than a certain number do not show in these figures. These vibration accelerations come from three sets of experiments, and the detail setup will be presented in section 3.1. For a particular spindle speed, two cutting depths are showed, one stable and one chatter, for comparison.

The RMS sequence has another advantage that it is free from the influence of occasionally spikes in the original signal. There are some spikes in the original signal, as indicated by red oval circles in Figs. 3 and 4. These spikes are averaged out after RMS sequence pretreatment. The parameter N is chosen based on sample frequency and signal character. On one hand, if it is set to be too small, then the spikes could bring fluctuation into the RMS sequence. On the other hand, if it is too big, then the RMS sequence may not reflect the dynamic change of the signal amplitude. Taking these factors into consideration, RMS is calculated every 0.2 s in this paper.

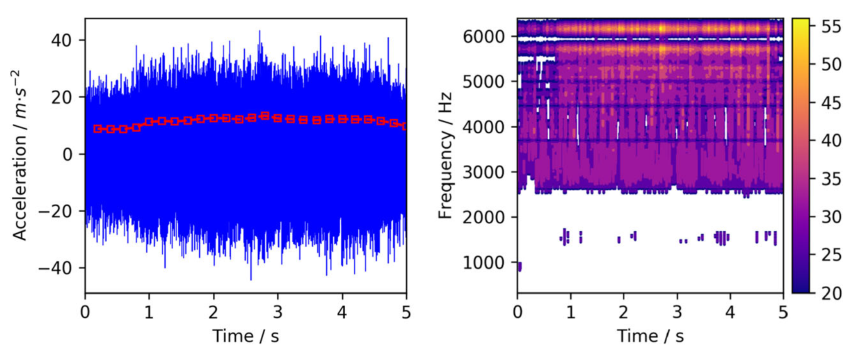


Fig. 2 Al-5a06, spindle speed = 9000 rpm, cutting depth = 2.1 mm, chatter. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 20 do not show in figure

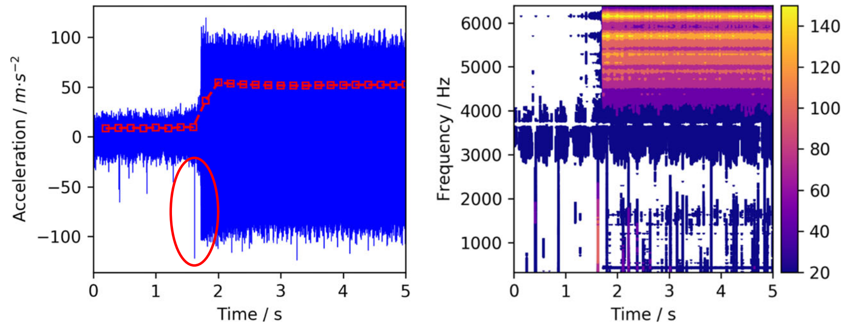


Fig. 3 Al-5a06, spindle speed = 10,000 rpm, cutting depth = 1.7 mm, chatter. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 20 do not show in figure

2.2 Coefficient of variation

By studying Figs. 1, 2, 3, 4, 5, 6, 7, and 8 and comparing the stable ones and chatter ones, the following can be found:

1. RMS sequence is more fluctuant when chatter occurs. In fact, since chatter is an unstable vibration of the spindle-tool-workpiece system, the vibration is bound to be more fluctuant.
2. When machining state transits form stable to chatter, frequency band migrates, in this particular experiment setting, to a higher band. By contrast, in stable machining process, it stays in the same band. In some cases, higher frequency components do show up when machining state is stable, e.g., Fig. 7, but the difference of coefficients between lower band, approximately 2500 to 4500 Hz, and the higher band, approximately 5000 Hz and higher, is small.
3. Notice that the time domain fluctuation and frequency domain migration show up in the same timeline. It reveals the tight link between time domain amplitude changes and frequency domain band migration.

Therefore, chatter can be identified by defining the appropriate parameters to describe the transition process from stable to chatter, whether time domain or frequency domain.

In machining process, machine tool and cutting parameters vary; hence, the vibration amplitude, frequency band migration, fluctuation degree of the chatter, and the transition process from stable to chatter are also different. To identify the machining state under different machining circumstances, coefficient of variation, CV, a dimensionless parameter, of RMS sequence is defined as chatter indicator, as shown in Eq. (2).

$$\mathrm{CV} = \frac{\sigma}{\mu} \tag{2}$$

where μ is the mean and σ is the standard deviation of RMS sequence, which can be calculated with Eqs. (3) and (4), respectively.

$$\mu = \frac{1}{n}\sum_{j=1}^{n} a_{\mathrm{RMS}j} \tag{3}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(a_{\mathrm{RMS}j}-\mu\right)^2} \tag{4}$$

Obviously, when machining state transits from stable to chatter, CV increases. CV can capture the process of transition. To determine whether the chatter occurs, a proper CV threshold needs to be selected. This paper will give the threshold based on experiment.

However, if machining process somehow does not experience this transition from stable to chatter, CV could fail. As shown in Fig. 9, from the very beginning of milling, the machining state is chatter. Under this condition, CV cannot detect chatter since there is no transition to capture.

Still, this problem can be tackled in other way. It will be shown later that a large RMS threshold can be used to distinguish this kind of situation. The challenge is how to set a proper threshold easily. We will come back to this in section 3.2.2.

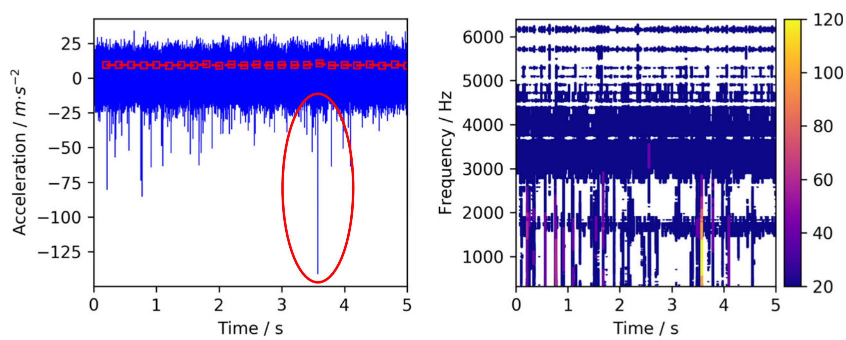


Fig. 4 Al-5a06, spindle speed = 10,000 rpm, cutting depth = 2.1 mm, stable. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 20 do not show in figure

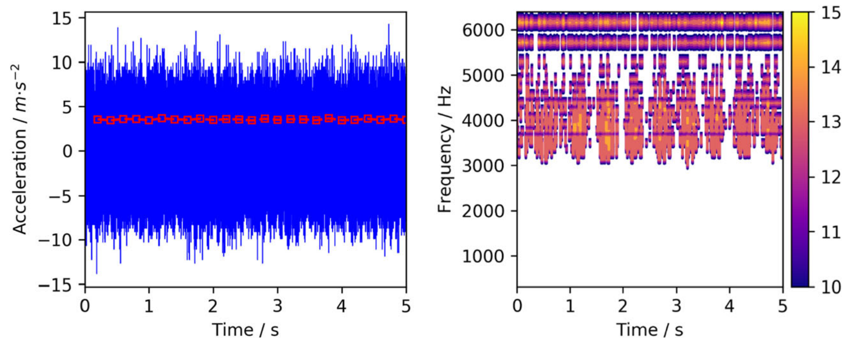


Fig. 5 Al-7075, spindle speed = 10,000 rpm, cutting depth = 0.5 mm, stable. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 10 do not show in figure

2.3 Chatter online monitoring

In actual machining process monitoring, it is always expected that the system can quickly identify chatter, which can be achieved by reducing the complexity of the algorithm. This problem can be expressed as to calculate the new mean and standard deviation when a new root mean square value is added to current RMS sequence, the mean and standard deviation of which are known.

Suppose that the current sequence contains n values, the mean is μ_n, and the standard deviation is σ_n. Now, adding a new value a_{RMS_n+1} to forms the new RMS sequence, with mean μ_{n+1}, standard deviation σ_{n+1}. According to definition,

$$\sigma_{n+1}{}^2 = \frac{1}{n}\left\{\sum_{i=1}^{n}\left(a_{\mathrm{RMS}\_i}-\mu_{n+1}\right)^2+\left(a_{\mathrm{RMS}\_n+1}-\mu_{n+1}\right)^2\right\} \tag{5}$$

Expand the right side of the Eq. (5), and substitute corresponding part with σ_n and μ_n,

$$\sigma_{n+1} = \left[\left(1-\frac{1}{n}\right)\sigma_n{}^2+\left(\mu_n-\mu_{n+1}\right)^2+\frac{\left(a_{\mathrm{RMS}\_n+1}-\mu_{n+1}\right)^2}{n}\right]^{\frac{1}{2}} \tag{6}$$

where

$$\mu_{\mathrm{n}+1} = \frac{n\mu_n+a_{\mathrm{RMS}\_n+1}}{n+1} \tag{7}$$

Then,

$$CV_{n+1} = \frac{\sigma_{n+1}}{\mu_{n+1}} \tag{8}$$

The length of the RMS sequence should be properly selected in the algorithm. The sequence should be long enough to reveal the fluctuation of the signal, but not too long, which could make the change of CV less obvious.

Based on the above analysis, we can design the online monitoring algorithm as shown in Fig. 10. In the algorithm, n tracks the length of the RMS sequence and controls the maximum length of the sequence with $n_{\max}$. The complexity of the algorithm is O(1), which enables fast and accurate chatter identification.

The RMS threshold in the diagram is to detect the situation that the machining state is chatter at the very beginning. This will be studied in more detail in section 3.2.2.

3 Experiment

3.1 Experiment setup

As shown in Fig. 11, the experiment was carried out on a DMG DMU60 five-axis vertical machining center. The vibration acceleration sensor (PCB triaxial modal acceleration sensor, model NO. 356A16) was mounted on the machine tool spindle box.

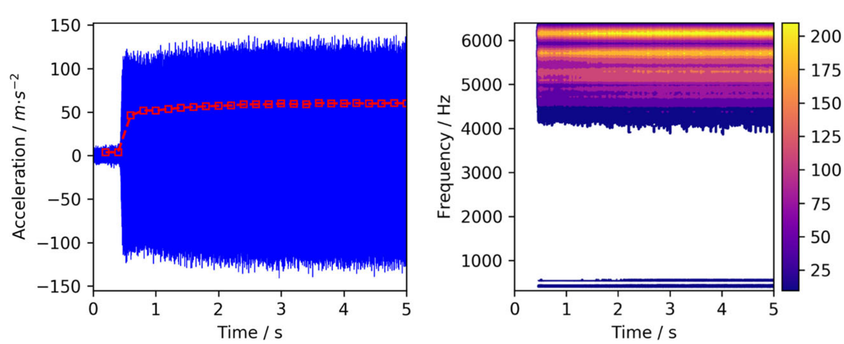


Fig. 6 Al-7075, spindle speed = 10,000 rpm, cutting depth = 1.8 mm, chatter. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 10 do not show in figure

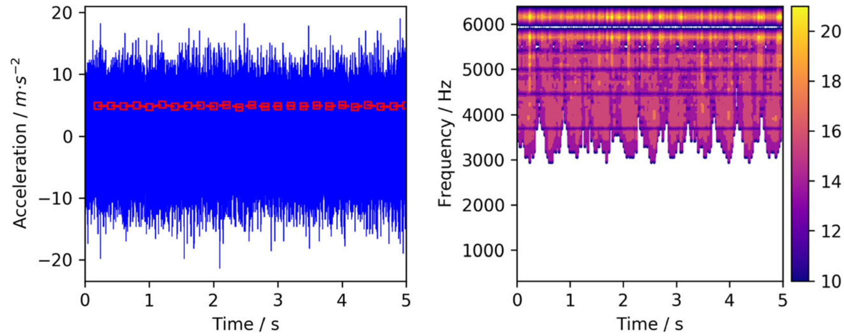


Fig. 7 TC4, spindle speed = 9000 rpm, cutting depth = 0.2 mm, stable. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 10 do not show in figure

Cutting tool material is carbide, with blade diameter of 8 mm, three blades, helix angle of 55°, and overhanging length of 35.5 mm. Data acquisition rate is 12,800 Hz, with sample time of 5 s.

Three sets of experiments on different materials were conducted with changing spindle speed and cutting depth. Using trial cutting method, the following parameter combinations are performed:

1. Experiment set 1, aluminum alloy 7075T6, with spindle speed ranging from 6000 to 12,000 rpm of every 1000 rpm. With every spindle speed, experiment with cutting depth of 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.50, 0.80, 1.20, 1.50, and 1.80 mm, a total of 84 experiments
2. Experiment set 2, aluminum alloy 5A06H112, with spindle speed ranging from 6000 to 10,000 rpm of every 1000 rpm. With every spindle speed, experiment with cutting depth of 1.3, 1.7, 2.1, and 2.5 mm, a total of 20 experiments
3. Experiment set 3, titanium alloy TC4, with spindle speed ranging from 3000 to 11,000 rpm of every 2000 rpm. With every spindle speed, experiment with cutting depth of 0.2, 0.4, 0.6, and 0.8 mm, a total of 20 experiments

Experiment sets 1 and 2 are conducted corresponding to full immersion and experiment set 3 corresponding to half immersion, up-milling. In total, they add up to 124 experiments.

3.2 Results and discussion

3.2.1 Coefficient of variation and machining state

The relationship between the machining state and CV value all fall in the same category, that is chatter state have a higher CV comparing with stable state, except three experiments, which will be discussed in detail in the next section. Disregarding these three, the relationship is shown in Fig. 12, which includes 121 experiments over 124. It can be seen from the figure when machining state is chatter, CV value is greater than 0.10, and when they are sable, CV value is far below 0.10, which makes 0.10 a good threshold for distinguishing machining state.

CV has a big gap between chatter and stable, and it can be used to formulate more sophisticated monitor plan. Of all chatter ones, CV is above 0.1, and of all stable ones, it is below 0.07. The value between 0.07 and 0.1 can be used as a pre-alert zone. If the monitoring strategy is conservative, this zone can be treated as chatter directly.

It also can be seen from Fig. 12 that CV works very well for different materials. Although both Al-7075 and al-5a06 are aluminum alloy, their machining properties are quite different, and titanium alloy is notoriously difficult to cut. Despite their huge differences, CV works well for them.

In our experiment, the TC4 set is conducted corresponding to half immersion, and because our cutting tool only has three blades, the loss of contact between tool and workpiece [36, 37] could come into play. Experiment sets 1 and 2 are

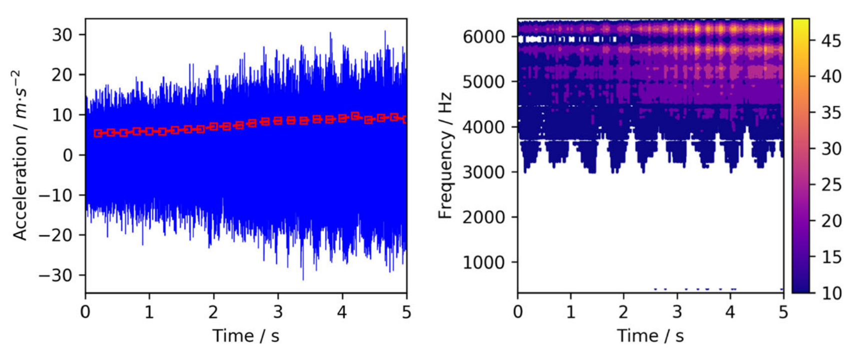


Fig. 8 TC4, spindle speed = 9000 rpm, cutting depth = 0.6 mm, chatter. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 10 do not show in figure

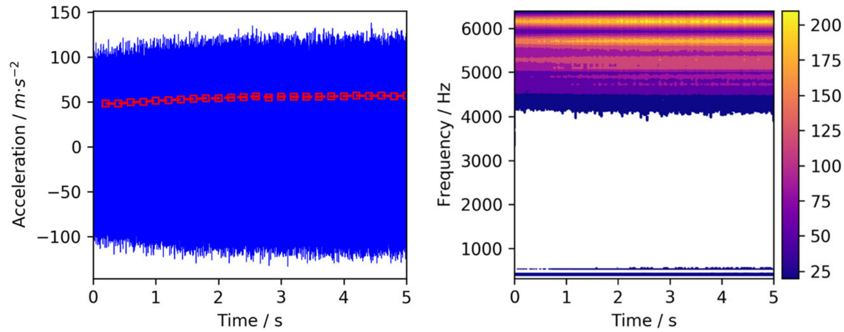


Fig. 9 Al-7075, spindle speed = 10,000 rpm, cutting depth = 1.5 mm, chatter. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 20 do not show in figure

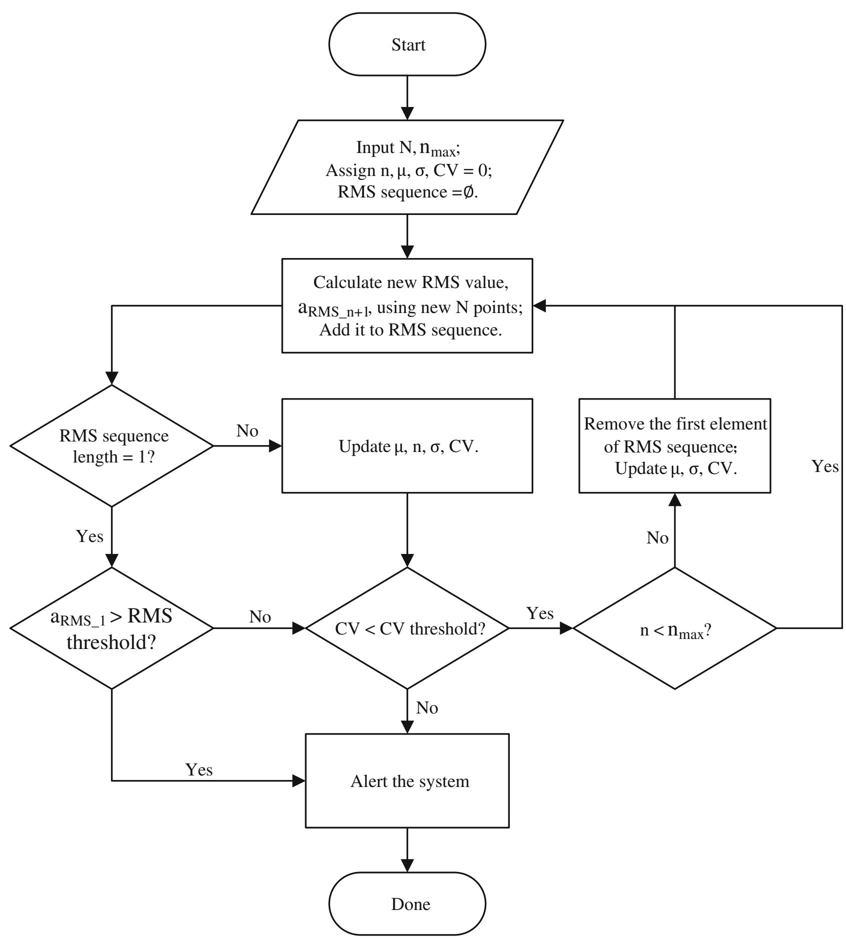
conducted in full immersion; hence, they do not have the loss of contact phenomenon. Obviously, the frequency of loss of contact is the same with tooth pass frequency, which is already a component of the vibration signal, so the loss of contact only adds some variation to this particular frequency component. The experiment shows that loss of contact does not affect the method we proposed. The wavelet transformation in Figs. 1, 2, 3, 4, 5, 6, 7, and 8 shows that the tooth pass frequency is insignificant in the machining vibration, whether the loss of contact exists or not. And results shown in Fig. 12 further corroborate the effectiveness of the method under this circumstance.

3.2.2 Detect intense chatter

Aluminum alloy 7075T6 experimental set, 59th and 71th experiments, and aluminum alloy 5A06H112 experimental set, 12th experiment, of which machining states are chatter, but the CVs are not large, 0.05, 0.03, 0.08, respectively, are shown in Table 1,

As shown in Figs. 9, 13, and 14, these three experiments are exactly the situation mentioned in section 2.2, i.e., the machining process does not have a transition from stable to chatter. At the very beginning of the machining, chatter occurs, as shown by high amplitude of time domain and high

Fig. 10 Chatter online monitoring algorithm



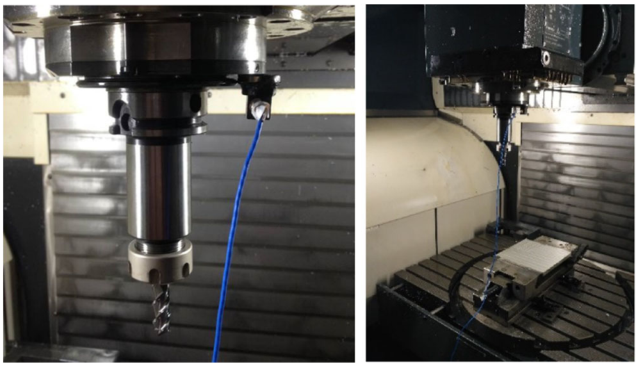


Fig. 11 Experiment setup

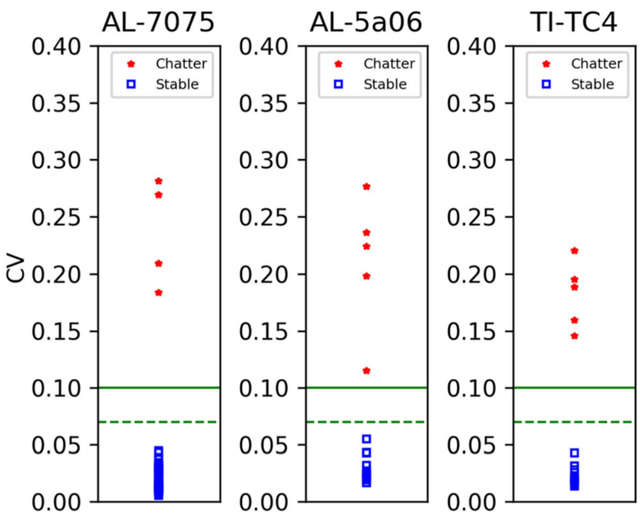


Fig. 12 CV value and machining state, the green dash line is at the level of 0.07

frequency band. Hence, the signals do not show the desired transition and the CVs of the RMS sequence are not large.

In practice, the situation of machining chatter at the very beginning is not so common. In most case, the machining is stable, the cutting is smooth, but suddenly, the machining changes to chatter duo to parameter changes or other reasons. The CV is suit for this common situation. To detect the rare circumstance exampled by these three experiments, other criterion needs to be developed. Since the vibration under this condition is tense, we refer them as intense chatter.

As shown in Fig. 15, when cutting is stable, all the RMS of acceleration only varies in a small range. But for different material, the range is quite different. Comparing RMS between stable cutting and the three experiments mentioned above, it can be seen that the RMS of these three is much higher. However, they are not positive related, that is for stable cutting, RMS of al-5a06 is higher than al-7075, but for intense chatter, RMS of al-7075 is higher, as shown in Fig. 15 and Table 1. Naturally, a RMS threshold can be set to identify the intense chatter situation. The problem is how to choose a proper one easily in practice.

When cutting is stable, RMS of acceleration can be viewed as a Gaussian distribution at every spindle speed. Under stable condition, the standard deviation σ is no bigger than 0.1μ, which is indicated by the CV threshold value. For a Gaussian distribution, it is generally considered that value out the scope of $\mu \pm 5\sigma$ is highly abnormal; hence, the upper bound is 1.5μ, when plug in $\sigma = 0.1\mu$. Therefore, 1.5μ can be chosen as RMS threshold.

As for μ, it varies among different spindle speed. To simplify the detection algorithm, the threshold is set the same for all spindle speeds. Since vibration differs between speeds, as shown in Fig. 16, and the threshold is the upper boundary, it should be set as the largest among different spindle speed. Based on this analysis, we propose the following way to acquire it quickly: for a particular material, conduct one stable cutting experiment at each commonly used spindle speed, and then chose the largest RMS of them as μ. In this way, only a few experiments need to be conducted to set this threshold. And once the system is up and running, more data is collected and then the threshold can be updated. Using the proposed method, the μ for al-5a06 and al-7075 is 9.4 and 6.0 m s^{-2}, respectively, so the correspond threshold is 14.1 and 9.0 m s^{-2}. The three experiment value is way above the threshold and can be detected correctly.

It is worth noting that we only check this threshold at the beginning of machining, and that is why the algorithm in Fig. 10 checks this only when RMS sequence length equals one.

3.2.3 Online monitoring

According to the analysis of the previous section, the threshold of the monitoring algorithm is set as 0.10. Figures 17, 18,

Table 1 Experiments that chatter with small CV

NO.	Spindle speed/rpm	Cutting depth/mm	Machining state	CV	RMS/m s^{-2}
Set 1–59	10,000	1.5	Chatter	0.05	54.4
Set 1–71	11,000	1.5	Chatter	0.03	67.4
Set 2–12	8000	2.5	Chatter	0.08	28.0

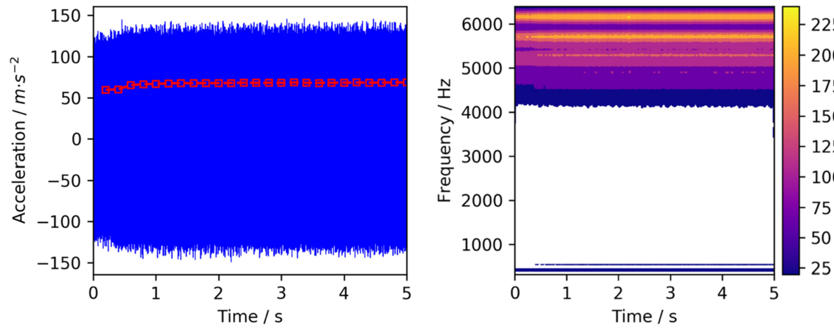


Fig. 13 Al-7075, spindle speed = 11,000 rpm, cutting depth = 1.5 mm, chatter. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 20 do not show in figure

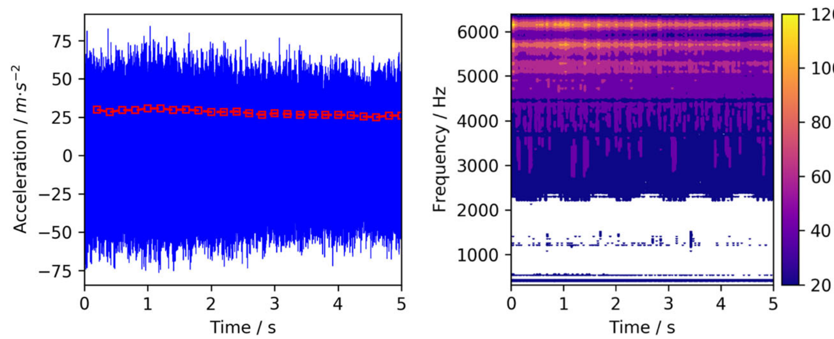


Fig. 14 Al-5a06, spindle speed = 8000 rpm, cutting depth = 2.5 mm, chatter. Left: acceleration and its RMS sequence, blue curve is the original, red curve is the RMS sequence. Right: continuous wavelet transformation of the original signal, coefficients less than 20 do not show in figure

19, 20, 21, and 22 give examples of the changing of CV during cutting. For each material, two experiments are presented for comparison. It can be seen from the picture that once the machining state exhibits transition from stable to chatter, the CV value soars above 0.10. Other experiments showed the same result, proving the method to be effective for online monitoring.

4 Conclusions

It can be concluded that when the machining state changes from stable to chatter, the vibration of the spindle-tool-workpiece system changes from stable to unstable, and the fluctuation is aggravated. Defining CV to capture this change achieves chatter recognition: during the machining process, obtain real-time RMS sequence of the vibration signal, and then calculate CV of that sequence, which achieves online real-time chatter monitoring. The proposed method has the following property:

As shown in the paper, there is a tight link between time domain amplitude changes and frequency band migration. Machining state changes result in time domain fluctuation and frequency band migration. This is why CV can capture the essence of machining state change from stable to chatter and identify chatter.

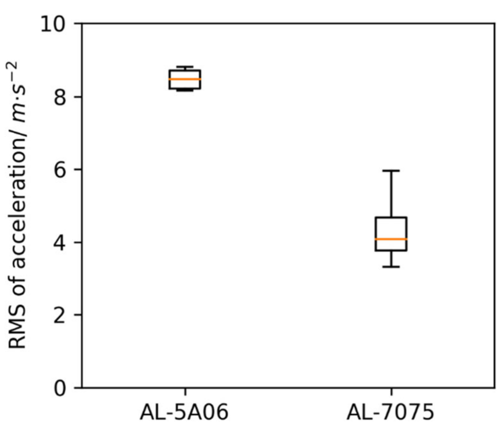


Fig. 15 Box plot of RMS for all stable cutting in the experiment

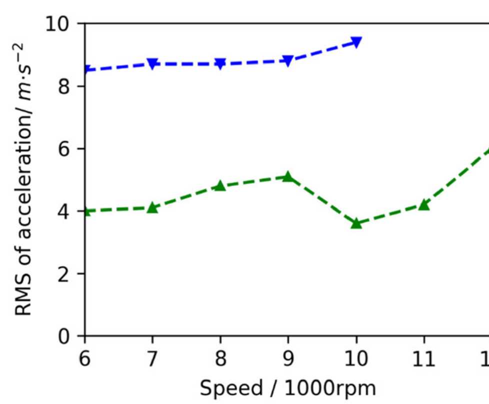


Fig. 16 RMS of acceleration at different spindle speed. Green curve: maximum RMS of al-7075 at different spindle speed; blue curve: maximum RMS of al-5a06 at different spindle speed

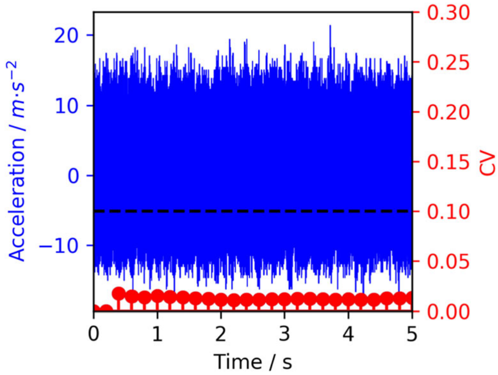


Fig. 17 Al-7075, spindle speed = 12,000 rpm, cutting depth = 0.25 mm, stable

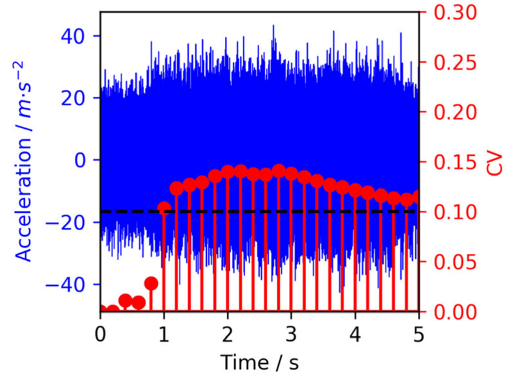


Fig. 20 Al-5a06, spindle speed = 9000 rpm, cutting depth = 2.1 mm, chatter

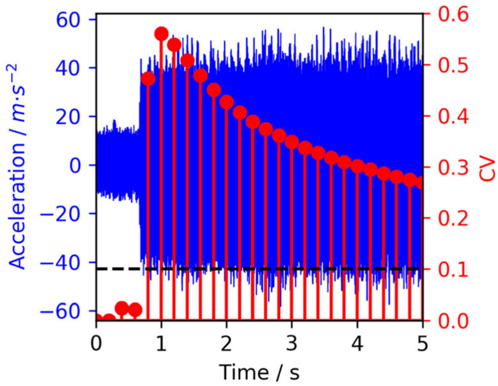


Fig. 18 Al-7075, spindle speed = 12,000 rpm, cutting depth = 0.3 mm, chatter

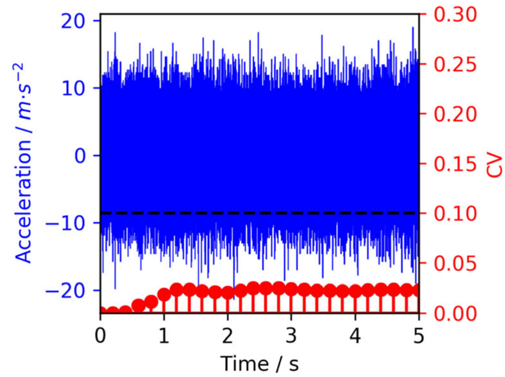


Fig. 21 TC4, spindle speed = 9000 rpm, cutting depth = 0.2 mm, stable

Since the method is based on the general character of chatter, it is very hopeful that it works even when the machine tool and cutting method are different, which of course need to be verified by more experiments.

As the method has a quantitative and dimensionless indicator, the threshold is all the same regardless of machining materials and machining parameters, making it extremely simple to apply it to real machining process.

The proposed fast algorithm of CV, reducing the computational complexity to O(1), is very suitable for online monitoring system.

The experiments show that the proposed method works well with different machining materials and

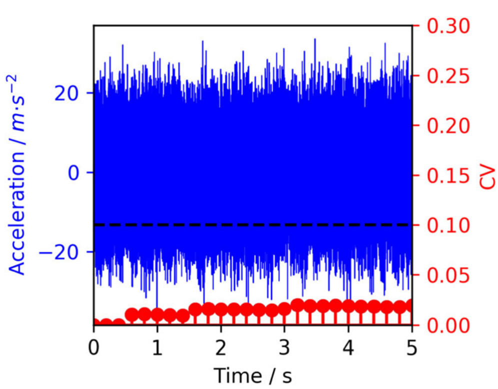


Fig. 19 Al-5a06, spindle speed = 9000 rpm, cutting depth = 1.7 mm, stable

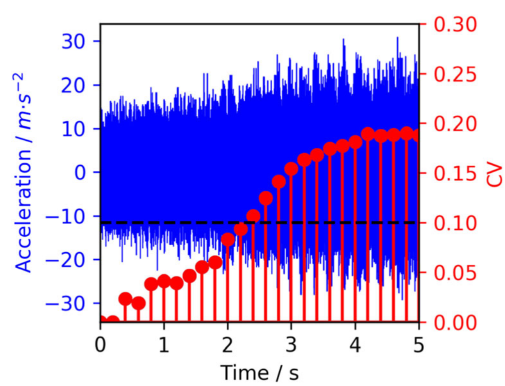


Fig. 22 TC4, spindle speed = 9000 rpm, cutting depth = 0.6 mm, chatter

machining parameters, proving the effectiveness and applicability of the method.

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