Online grinding chatter detection based on minimum entropy deconvolution and autocorrelation function

Dan He1 · Zexing Ni2 · Xiufeng Wang2

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Abstract
On-line detection of chatter is one of the key techniques to avoid the harmful effects caused by chatter in grinding process. The key to chatter detection is to capture reliable chatter features and thresholds. To achieve this, it is important to make clear and extract the essential characteristics of the grinding chatter signal, which has not yet been well studied. In this paper, we are going to investigate the essential characteristics of the grinding chatter signal and propose a new approach for on-line detection of grinding chatter. The proposed approach for on-line detection of grinding chatter is based on minimum entropy deconvolution and autocorrelation function, in which the minimum entropy deconvolution is employed to deconvolve the effect of transmission path, and further to restore the essential characteristics of the chatter signals. To eliminate the interference of the non-periodic impulse signals in the measured vibration signals, an autocorrelation function is introduced. Kurtosis is employed to indicate chatter according to the changes of the processed signal. The validity of the proposed method is demonstrated through the measured vibration signals obtained from grinding processes and the presented chatter detection index is independent from the grinding conditions with excellent detection accuracy and permissible computational efficiency. This demonstrates the effectiveness of proposed method in on-line implementation.

Keywords Chatter detection · Grinding · Minimum entropy deconvolution · Autocorrelation function

1 Introduction
Chatter is a kind of self-excited unstable vibration during the machining process [1]. Typically, the chatter encountered in machining is of the regenerative type, that would detrimentally affect the form accuracy and surface finish of the ground workpieces in the grinding process [2, 3]. On-line identification and isolation of the onset of chatter can prevent machining processes from the occurrence of these defects [4, 5]. Given the chatter features are submerged by forced vibration and noise in the initial stage of chatter occurrence, the key point to realize early chatter identification is to extract the essential characteristics of the chatter signals. To a great extent, these demands rely on the measured signal type and feature extraction technique.

Over the years, many kinds of sensor signals have been used to monitor chatter, such as acceleration signal [4], sound [5], motor current [6–8], torque signal [5], and acoustic emission signal [9]. In [5], several sensors were compared to determine which signals are most sensitive to chatter onset by Kuljanic. The results indicate that force signals are more sensitive to chatter than other sensor signals since the time-varying cutting force is the root of chatter. However, it is difficult to apply the force transducer in industrial conditions since it is not compatible with the tool changer, which may reduce the system stiffness.

However, the acceleration sensor is usually used for flutter detection as it is easy to install and higher the signal-to-noise ratio of the signal. In this paper, the acceleration signals of the machine tool are used for chatter detection. No matter what kind of sensors are chosen, the feature extraction technique
is much more important, and it is the focus of the remainder of this paper. At present, many feature extraction methods have been developed for chatter detection, and these detection methods can be classified into two kinds. One is based on the changes in the characteristics of feature signals, which are sensitive to chatter occurrence, and the other is based on the changes in machining dynamics caused by the onset of chatter. For the former one, spectral analysis [1], wavelet [4, 6], correlation analysis [8], ensemble empirical mode decomposition [10], and Hilbert–Huang transform [4] are introduced to identify chatter according to the change of time–frequency characteristics of the measured signals. The latter chatter detection principle uses coarse-grained entropy rates [11], coarse-grained information rate [12], and summed non-stationary wavelet bispectrum feature [7] as the indicators which reflect the change of the dimensional dynamics during machining. A review of other methods for chatter detection is given in [13].

Although many feature extraction methods have been used for chatter detection, the chatter threshold selected of existing methods is empirical and not valid over a wide range of processing conditions. Therefore, these methods are mostly not suitable for on-line chatter detection. To solve the problem that the chatter threshold cannot be easily determined. It is necessary to reveal the essential characteristics of the measured chatter signal. Chatter is a kind of self-excited vibration, and the main source of the self-excited chatter vibrations in grinding is also due to the regenerative effect [13–15]. The theory of regenerative chatter explains that the machine structure is excited in the range of its dominant natural frequencies, which are reflected in the form of waviness on the surface of the workpiece. When the next part of the grinding wheel is grinding on this surface, it leads to a renewed excitation of the machine structure. The process becomes unstable when the damping in the system is insufficient. In [14], the simulation result shows that grinding force is a periodic impact signal when grinding chatter occurred, and the period of grinding force is equal to the rotational period of the spindle. Besides, a lot of research efforts have indicated that chatter frequencies are close to the mechanical natural frequencies of machine tools, and more than one dominant frequency can appear, each of which is approximately a multiplicity of the wheel rotational frequency; if machine operation is stable, these frequencies do not arise [13, 15, 16]. Consequently, according to the previous chatter studies, vibration mechanics, and digital signal processing (Fast Fourier Transform and convolution properties), we can conclude that the measured chatter signal should be a convolution result of the periodic impact forces and natural frequencies of machine tools. To better understand the above content, the production process of a simplified chatter signal can be described as in Fig. 1.

![Fig. 1 Produce process of a simplified chatter signal](image-url)
signal, which makes chatter detection difficult. To reduce the spread of the convolution process, the minimum entropy deconvolution (MED) method is introduced here. The MED method is developed to reduce the spread of the impulse response frequencies by Wiggins [17], it can effectively restore the original impulses. In this paper, we focus on the effect of the transmission path during chatter detection. The MED is employed to deconvolve the effect of transmission path, and restore the essential characteristics of the chatter signals. A new approach for on-line detection of grinding chatter is proposed based on MED and autocorrelation function. The proposed approach is validated with comprehensive experimental data under various grinding conditions, and the presented chatter detection index is independent of the grinding conditions.

The remainder of the paper is organized as follows: Sect. 2 describes the theoretical background, Sect. 3 addresses the anti-interference capability of the MED method will be discussed. Section 4 introduces the proposed approach. Section 5 presents the effectiveness of the proposed approach with validation results using various experimental data. Section 6 concludes this paper.

2 Theoretical background

2.1 Minimum entropy deconvolution

Minimum entropy deconvolution (MED) was firstly proposed for application in analyzing seismic recordings by Ralph Wiggins in 1978 [17], and it has been evaluated for its effectiveness in extracting the hidden impulse signals from a mixture of response signals [18–20]. The basic idea of MED is to find an inverse filter that counteracts the effect of the transmission path [21]. It is designed to reduce the spread of the impulse response signal, and then obtain the signal which is closer to the original impulse signal.

Figure 2 shows the basics of the MED method. The impulse signal $e(t)$ passes through the structural filter $h$ whose output is mixed with noise $n(t)$ to give the measured output $x(t)$. This is a convolution process of the impulse signal and the resonance frequency band of the component. The inverse filter $f$ produces output $y(t)$, which has to be as close as possible to the original input $e(t)$. This process eliminates the influence of the structure resonance. The input $e(t)$ is unknown, so it is assumed to be as impulsive as possible.

The inverse filter $f$ is modeled as an FIR filter with length of the filter $L$ and we have

$$y(t) = \sum_{l=1}^{L} f(l)x(t-l)$$

where $f(l)$ has to invert the system IRF $h$ such as:

$$f(l) * h(t) = \delta(t - l_m)$$

The delay $l_m$ is such that the inverse filter can be causal. It will displace the whole signal by $l_m$ but will not change the pulse spacing.

The inverse filter $f$ was implemented by maximizing the kurtosis of the output signal $y(t)$ [22]. The kurtosis is taken as the normalized fourth-order moment given by:

$$O_4(f(l)) = \sum_{i=1}^{N} y^4(t)/\left( \sum_{i=1}^{N} y^2(t) \right)^2$$

and the maximum kurtosis of $y(t)$ can be obtained according to $f(l)$ for which the derivative of the objective function is zero such as:

$$O_4(f(l))/f(l) = 0$$

2.2 Autocorrelation function

The autocorrelation function is an important diagnostic tool for analyzing time series in the time domain. The autocorrelation function as defined by Eq. (5) is the average product of the sequence $x(t)$ with a time-shifted, version of itself.

$$R_{xx}(\tau) = E\{x(t) x(t+\tau)e^{-j2\pi\omega_0}\} = \lim_{T\to\infty} \frac{1}{T}\int_{-T}^{T} x(t)(t+\tau)dt$$

where $x(t)$ is jointly stationary random processes, $x$ is length $T$ vectors. $R_{xx}(\tau)$ returns the autocorrelation sequence in a length $2T-1$ vector, $t = 1, 2, \ldots, 2T-1$. $E\{\bullet\}$ is the expected value operator.

In this paper, unbiased autocorrelation is employed to extract periodic impulse response signals from a filtered signal contains a bigger non-periodic impact response signal. The unbiased autocorrelation function is defined by Eq. (6).

$$R_{xx\text{unbiased}}(\tau) = \frac{1}{T-|\tau|} R_{xx}(\tau)$$
The anti-interference capability of the MED method

The MED method has shown its effectiveness in fault diagnosis of gears and bearings [18]. But for on-line chatter detection, the robustness of the proposed method is very important. Here, the anti-interference capability of the MED method will be discussed.

3.1 Simulated signal

In the machining process, there are usually some non-periodic interference signals in the measured vibration signals. A simulated signal is generated according to the characteristics of the chatter signal, and the simulated signal contains a bigger non-periodic impact signal. The simulated signal can be expressed by Eq. (7).

\[
x(t) = \sum_{i} s_{1i} e^{-\zeta t/T_{1i}} \cdot \cos(2\pi f_{ni} (t - iT_{1i})) + \sum_{i=25} s_{2i} e^{-\zeta t/T_{2i}} \cdot \cos(2\pi f_{ni} (t - iT_{2i})) + 0.5 \cdot \cos(2\pi f_{1i} t) + 0.5 \cdot \cos(2\pi f_{2i} t) + n_{\text{noise}}(t)
\]

The simulated signal \(x(t)\) is composed of five terms. The first term represents a series of the periodic impulse signals excited by chatter, it is a convolution result of the periodic impact signal and natural frequencies of machine tools, where \(s_{1i}\) is the amplitude of the periodic impulse signal and \(T_{1i}\) is the rotation period of the grinding wheel, \(\zeta_{1}\) is a resonance damping coefficient depending on the exciting structure, \(f_{ni}\) is the natural frequency of the exciting structure. The second term represents a bigger non-periodic impact response signal from unknown sources, it is a convolution result of the non-periodic impact signal and unknown natural frequencies. The third and fourth terms represent the fundamental frequency, \(f_{1i}\) is the fundamental frequency. The fifth terms denote the measurement noise. The parameters of simulated signals \(x(t)\) chosen are shown in Table 1.

In this simulation, the signal to noise ratio (SNR) of the periodic impulse response signal is \(-5.74\) dB. The sampling frequency is 2048 Hz and the time length of data is 1.5 s. Produce process of the simulated signal is shown in Fig. 3.

Figure 3 describes the production process of the simulated signal. Figure 3a shows the convolution process weakens the impact characteristics of the simulated signal, and Fig. 3b shows the fundamental frequency and white noise further weaken the impact characteristics of the simulated signal.

### Table 1: The parameters of the simulated signal

| \(1/T_{1i}\) (Hz) | \(1/T_{2i}\) (Hz) | \(f_{ni}\) (Hz) | \(f_{1i}\) (Hz) | \(f_{2i}\) (Hz) | \(s_{1}\) | \(s_{2}\) | \(\zeta_{1}\) | \(\zeta_{2}\) |
|-----------------|-----------------|-----------------|----------------|----------------|--------|--------|--------|--------|
| 53              | 60              | 350             | 700            | 50             | 175    | 1      | 10     | 120    |

3.2 Analysis of the anti-interference capability of the MED

Based on the analysis above, the algorithm of MED in literature [7, 17] was used, and the length of the filter \(L\) was selected at 30, the termination number of iterations was selected at 30, and termination threshold of iterations was selected at 0.01 [18]. Figure 4 depicts the simulated signal filtered with the MED method.

It can be seen that periodic impulse characteristics can be observed after the MED method in Fig. 4. It demonstrates the MED method has the anti-interference ability in filtering chatter signal.
To eliminate the interference of the non-periodic impulse signals, the unbiased autocorrelation function can be used to extract periodic impulse characteristics from the measured signals. Figure 5 shows the unbiased autocorrelation of two signals.

Figure 5 shows the unbiased autocorrelation from a raw signal and MED filtered signal in the time domain. The details of Fig. 5a depict the periodic impulse characteristics are not recognizable after unbiased autocorrelation of the raw simulated signal; however, the details of Fig. 5b depict the periodic impulse characteristics are quite significant after unbiased autocorrelation of the MED filtered signal. It indicates that the unbiased autocorrelation of the MED filtered signal can effectively restore the periodic impulses. Besides, it should be noted that the unbiased autocorrelation sequences are both symmetrical about the center and maybe distorted on both ends; hence, the unbiased autocorrelation sequences should be selected to describe the characteristics of periodic impulse in a length $T/5$, $t = T/5, \ldots, 2T/5$.

4 The procedure of the chatter recognition method

The essential characteristics of the measured chatter signal have been discussed and conclude that the measured chatter signal is a convolution result of the periodic impact forces and the natural frequencies of machine tools. To reduce the spread of the convolution process, the MED is employed to deconvolve the effect of the transmission path, and restore the impact feature of the chatter signals. The autocorrelation function is introduced to extract periodic impulse characteristics. Kurtosis is employed to indicate chatter.

Kurtosis is a measure of the heaviness of the tails in the distribution of the signal $x(t)$. Outlier or abrupt changes in $x(t)$ have high values and accordingly appear in the tails of the distribution [23]. This means that the impulse signal is of very high Kurtosis while the sinusoid and noise signal is of very low Kurtosis. What’s more, the normal distribution, with a value of kurtosis equal to 3, is often used as a standard. Impulse signal presents a much wider distribution, with a value of kurtosis greater than 3. Therefore, kurtosis can be employed to indicate chatter according to the changes of distribution of the processed chatter signal, and the detection index is independent of the grinding conditions.

The flow chart of the proposed method is shown in Fig. 6, and the implementation of the proposed method is summarized as follows:

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**Fig. 5** (a) The unbiased autocorrelation of the raw simulated signal. (b) The unbiased autocorrelation of filtered signal with MED method
Step 1: Slice the original signal using the rectangular window function.
Step 2: Deconvolve the effect of the transmission path of each vibration signal using MED, and restore the essential characteristics of the chatter signals.
Step 3: Extract periodic impulse signals using unbiased autocorrelation, and the unbiased autocorrelation sequences should be selected to describe the characteristics of periodic impulse in a length $T/5, t = T/5, \ldots, 2T/5$.
Step 4: Calculate the kurtosis of each unbiased autocorrelation sequence ($K_M$).
Step 5: Chatter recognition through comparing $K_M$ with threshold. Chatter state normally has a value of $K_M$ greater than 3, and a proper threshold should be selected for more accurate chatter detection according to the analysis results of experimental data in the next section.

5 Experimental validation

5.1 Experimental setup

The experiments were performed on a worm wheel gear grinding machine YK7230, which uses a 3-phase AC PMSM to drive the worktable. The grinding machine is composed of 11 axes, with five axes moving synchronously during the grinding process, such as 3 translational axes (X, Y, Z), grinding wheel axis (B axis), and worktable axis (C axis). Figure 7 shows the grinding machine mechanical structure and its kinematic principles. The experimental setup is illustrated in Fig. 8. A 3-axis piezoelectric acceleration sensor (356A15, PCB, USA) was placed at the free end of the grinding wheel axis to measure the vibration of the tool. The gear is made of C45 with 70 teeth and a module of 3 mm. The helix angle is 0 degree. The signal acquisition module is DT 9837B, which was used to collect acceleration signal. The sample rate was 2560 Hz. Oil-based coolant was used throughout the grinding process.

Two grinding tests were selected to verify the effectiveness of the method. Test 1 is a constant machining, consisting of 4 grinding strokes, spindle speed $n = 4000$ rpm and transverse feed rate $f = 0.12$ mm / stroke. There are four random impulse in the measured signal. Test 2 is variable machining, which is a complete machining process, including 4S coarse grinding, 1S semi-finish grinding, and 1S finish grinding. The processing parameters are shown in Table 2.

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Fig. 6 The flow chart of the chatter recognition method

Fig. 7 Machine tool structure.
(a) Kinematic diagram. (b) Gear grinding movement
The mechanical natural frequencies of the grinding carriage are measured by impact hammer testing, and Fig. 9 illustrates the natural frequencies of the grinding carriage; it can be noted that there are two dominant modes whose natural frequency is 308.6 Hz and 921.7 Hz respectively.

5.2 Application results

In this section, the ability of the proposed method to resist random impact and the generalization ability under variable speed conditions are verified respectively. The root mean square (RMS) and envelope spectrum energy [24] are used for comparison.

5.2.1 Analysis for the resistance to random impulse

Figure 9 shows the time waveform and short-time Fourier transform (STFT) spectrograms of the measured signals during the coarse grinding processes. In the coarse grinding process, the gear was usually ground four times with spindle speed \(n = 4000\) rpm and transverse feed rate \(f = 0.12\) mm/stroke. In Fig. 10a, it can be seen that the grinding process seems to be stable at each stage, and there are four random impulse at stage one and stage two. Figure 10b shows the STFT spectrograms of the measured signal. There are obvious equal interval frequencies in the STFT spectrogram in stage two, stage three, and stage four, and the interval is the spindle rotation frequency. Based on the chatter signal characteristics discussed in Sect. 1, it is proved that grinding chatter occurred in stage two, stage three, and stage four.

Furthermore, the proposed method was used to detect chatter. As shown in Fig. 11, a window size of \(L_w = 1280\) samples were used to truncate the raw vibration signal, and the calculation time of each sequence is about 0.17 s. The time waveform of the preprocessed signal was shown in Fig. 11. In Fig. 11, the periodic impact caused by chatter can be obviously observed in stage two, stage three, and stage four of coarse grinding in the signals processed by MED, and which has not been observed in stage one. This is consistent with the analysis result in Fig. 10b.

Figure 12 shows four monitoring indicators of coarse grinding process. Figure 12a is the kurtosis after Med unbiased autocorrelation processing, AC-kurtosis. Figure 12b is the kurtosis obtained by MED. AC kurtosis is 3 in stage one, while AC kurtosis increases obviously in stage two, stage three, and stage four, which is consistent with the variation law of chatter. In Fig. 12b, there

| Table 2 Process parameters |
|---------------------------|
| Grinding stage            | Feed rate (mm/stroke) | Grinding wheel speed (rpm) |
| Coarse grinding (4S)      | 0.12                  | 4000                        |
| Semi-finish grinding (1S) | 0.06                  | 4000                        |
| Finish grinding (1S)      | 0.03                  | 2000                        |

Fig. 9 The natural frequencies of the grinding carriage
are four kurtosis mutation points, and the change trend of this index is different from that of chatter. It can be found that the kurtosis after autocorrelation treatment has better impact resistance. Figure 12c, d respectively showed RMS and spectral entropy after MED and unbiased autocorrelation processing. Compared with AC kurtosis, the change trend of RMS and spectral entropy is less consistent with the change of chatter. It demonstrates that AC kurtosis can effectively detect chatter, and 5 can be easily chosen to be a proper threshold value in this process.

5.2.2 Analysis for the variable conditions

The vibration signal of a complete grinding process was used to verify the effectiveness of the proposed method under variable working conditions. The grinding parameters selected in this study are summarized in Table 2. The
The time waveform and short-time Fourier transform (STFT) spectrograms of the measured signals are shown in Fig. 11.

In Fig. 13, the chatter can be identified in the coarse grinding stage two, stage three, stage four, semi-finish grinding, and the latter process of finish grinding. The unbiased autocorrelation of the MED filtered signal is shown in Fig. 14, and the periodic shocks were observed in the coarse grinding stage two, stage three, stage four, semi-finish grinding, and the latter process of finish grinding, which is consistent with the conclusion in Fig. 13.

The monitoring results of the four indicators on the whole grinding process are shown in Fig. 15. Compared with the kurtosis after MED, RMS, and spectral entropy after MED and unbiased autocorrelation, AC-kurtosis is more consistent with the occurrence of grinding chatter. It can be found that the proposed method has better monitoring ability for grinding chatter.
6 Conclusions

Focusing on the problem of grinding chatter monitoring, the action mechanism of chatter in vibration signal was analyzed. An adaptive flutter monitoring method based on MED and unbiased autocorrelation was proposed. Experiments under both constant and variable machining conditions are conducted to verify the efficacy of the proposed method. The numerical and experimental results showed that (1) the measured chatter signal should be a convolution result of the periodic impact signals and natural frequencies of machine tools. (2) The chatter information can be extracted adaptively and completely by MED, and the disturbances in the individual signal can be eliminated simultaneously with cross unbiased autocorrelation. This can improve the chatter information extraction automation and adaptability a lot; therefore, higher accuracy and robustness of chatter detection can be achieved. (3) The presented chatter detection index (AC- kurtosis) is independent of the grinding conditions and gives excellent detection accuracy and permissible computational efficiency, which makes it suitable for on-line implementation.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Dan He, Zexing Ni, and Xiufeng Wang. The first draft of the manuscript was written by Dan He and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability Our data was acquired from Qinchuan Machine Tool Group Co., Ltd. China. We signed a confidentiality agreement, so we are very sorry that the test data cannot be shared.

Declarations

Competing interests The authors declare no competing interests.

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