Int J Adv Manuf Technol (2016) 83:1801–1810
DOI 10.1007/s00170-015-7687-9

ORIGINAL ARTICLE

# Early chatter detection in gear grinding process using servo feed motor current

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Received: 1 April 2015 / Accepted: 3 August 2015 / Published online: 18 August 2015


**Abstract** Monitoring and early detection of chatter are the key techniques to avoid the harmful effects caused by chatter in manufacturing process. The key for early chatter detection is to capture the feature signatures. A convenient and reliable technique is presented in this study to detect chatter in gear grinding process based on servo feed motor current and wavelet packet transform. Wavelet packet transform was used to monitor the energy change in the frequency domain and to identify the feature frequency band with respect to chatter, the result of which was confirmed by the impact hammer test. Standard deviation and energy ratio of the feature frequency band signal were chosen as the indexes of chatter monitoring. Combining these two chatter features, the state of the grinding process could be classified and chatter could be detected reliably in industrial application with proper thresholds. Acceleration signals of the machine tool were used as a reference to compare with the results from current signals. In every stage of the grinding process, the feature frequency band signals of current and vibration signal have shown very coincident variation trend. Both theoretical analysis and experimental results manifested the feasibility and efficiency of the proposed method.

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**Keywords** Chatter detection · Grinding · Feed motor current · Feature frequency band · Wavelet packet transform

## 1 Introduction

Chatter is a kind of self-excited instable vibration during machining process, which always leads to multiple negative effects. The high complexity of mechanism and phenomenon makes it very difficult to understand chatter completely. Therefore, avoidance of chatter in manufacturing process has become a necessary and important requirement for manufacturers. Traditionally, two kinds of strategies are employed to achieve this target. One is to select proper machining parameters, and the other is to change the mechanical system's dynamic behavior [1]. However, it is always difficult to apply these methods in practice due to many factors, such as the frequent change of workpiece and machining parameters, the movement of the tool holder and worktable, the dullness of the tool, and so on. The only reliable strategy is to identify the machining status automatically by online monitoring, recognizing the occurrence of chatter, and suppressing it with efficient measures. Therefore, monitoring and detection of chatter are the foundation and key to avoid chatter in manufacturing.

In view of industrial practical application, a chatter detecting system should be with high precision, high reliability, low cost, and high usability. To a large extent, these demands rely on the signal type chosen to monitor. The signals often used for chatter monitoring are vibration, current, acoustic emission, cutting force, cutting torque, sound, and power. Kuljanic [2] used an approach based on multi-sensors to detect chatter in milling. The results indicate that cutting torque is influenced by chatter significantly since it is proportional to the uncut chip thickness, which is perturbed by the regenerative effect. Therefore, reliable chatter indicators can be derived from the cutting torque signals. However, it is difficult to apply the rotating dynamometer in industrial conditions since it is not compatible to the tool changer, which may reduce the stiffness of the system and limit the selection of cutting parameters. At the same time, it is expensive. The use of microphones for capturing and analyzing the cutting sound has been demonstrated to be an efficient and cheap solution [3]. However, one drawback is that the sound coming from other machines of the factory will make the received sound signal have a low signal to noise ratio (SNR).

Recently, researchers also began to detect chatter occurrence in turning and milling process with current signals. Compared with other signals, the drive motor current has several remarkable advantages, such as easier to acquire, low transducer cost, convenient to set up, and no interference with the machining environment. Based on those properties, a lot of work has been done on cutting force, tool-wear, tool-breakage detection, and other machining status monitoring by using motor current [4–8]. The current signals utilized for chatter detection could be spindle motor current or feed motor current. For milling process, the spindle inertia is small; thus, the spindle current is sensitive enough to be used to detect chatter [9]. As for machining process with large inertia spindle, like heavy duty numerical control (NC) vertical lathing or grinding, the power used to remove the workpiece material is only a part of the total spindle power. Therefore, the spindle motor current is insensitive to the change of cutting state, leading to the loss of high-frequency machining state information. However, the feed motor current is sensitive to the change of cutting force and cutting state. Accordingly, we can use the feed motor current to monitor and detect chatter in heavy duty turning and grinding process. Liu [10] proposed a cutting state monitoring method based on feed motor current in turning, which has an identification accuracy rate of above 95 %. As stated above, motor current can be used as an excellent indicator for chatter detection.

Wavelet analysis has been widely used in chatter monitoring field [11, 12]. Gonzalez-Brambila [13] used discrete wavelet transform (DWT) to analyze waviness on the workpiece surface in outer diameter grinding to monitor the amplitude and location of chatter. Choi [14] used a wavelet-based maximum likelihood estimation algorithm to calculate a chatter detection index. Yao [15] used wavelet packet transform (WPT) to extract chatter feature vector and designed a support vector machine (SVM) for pattern classification. Cao [16] proposed a chatter identification method for end milling based on WPT and Hilbert–Huang transform (HHT).

Recently, Quintana and Ciurana [1] reviewed the research achievement of chatter in machining process in detail. It is pointed out that the key of chatter monitoring is to detect chatter when it just begins and is not completely developed; therefore, the negative effect caused by chatter can be suppressed as much as possible. However, in the initial stage of chatter occurrence, the chatter features are submerged by forced vibration and noise. Thus, the key point to realize early chatter identification is to extract the feature frequency band signal where chatter information concentrates and based on that relevant analysis can be conducted.

However, in the realistic condition, chatter frequencies are very complicated, which are related to the damped natural frequency of the mechanical system. In milling process, they are also connected to the tooth pass excitation frequency and its higher harmonics [17]. In grinding process, the chatter frequency varies along with the grinding process which has strong nonlinear behavior character [18]. As a result, the chatter frequency band is usually selected based on experience almost lacking precise criterion [16].

This paper proposed a convenient and reliable grinding chatter detection technique based on servo feed motor current and an analytical method to identify the chatter frequency band. The rest of the paper is organized as follows. Section 2 briefly summarizes the study on chatter in grinding and its detection problem. The theoretical background of chatter detection by using servo feed motor current is stated in Section 3. Section 4 presents the scheme of the proposed chatter detection technique based on WPT. Section 5 introduces the experimental setup. In Section 6, the results and discussion of the proposed chatter detection technique are given and the acceleration signals are used as a reference to compare with the results. Finally, the conclusions are given in Section 7.

## 2 Chatter in grinding and its detection

The stability and monitoring of chatter vibrations in grinding was reviewed in a CIRP key note paper by Inasaki and Karpuschewski [19], and the time domain simulation of grinding chatter was reviewed by Altintas and Weck [20]. Among the various conceivable reasons for process instability in grinding, the regenerative effect is considered to be the major cause. Due to the rotational motion of the workpiece during the material removal process, the waves generated on the workpiece surface created by the relative vibration between the grinding wheel and the workpiece result in a change of depth of cut after one revolution of the workpiece. The phase shift between the surface waves and the current relative vibration makes the process unstable when a certain condition is reached. According to the position where regenerative waves generated, it can be divided into workpiece regenerative chatter and grinding wheel regenerative chatter. The increase rate of vibration amplitude for wheel regenerative chatter is much slower than that of workpiece regeneration type. Compared with cutting process, grinding is much more complex with multi-point contact and the characteristic parameters of grinding dynamics which are not generally necessary to consider in cutting dynamics, such as the contact stiffness of the grinding wheel and the grinding damping. As a result, there have been fewer research reports on grinding chatter than on cutting chatter like turning and milling.

Basically, the principles to achieve chatter detection can be classified into two kinds. One is based on the changes of the characteristics of feature signals which are sensitive to chatter occurrence, and the other is based on the changes in grinding dynamics caused by the onset of chatter. For the former one, the signals often used are acoustic emission, acceleration, and grinding force [21, 22]. Chatter will excite harmonics of grinding wheel spindle or workpiece axis rotational frequency in the feature signal according to the frequency domain analysis of regenerative chatter [19]. The latter chatter detection principle uses the coarse-grained entropy rate [23] or the coarse-grained information rate [24] as the indicators which reflect the predictability of the process.

To sum up, it can be concluded that although many different approaches have been taken to detect chatter from process quantities, it is basically only acceleration sensors and to some extent AE systems that have found greater industrial acceptance. All the other sensor systems are restricted to laboratory use either because of the complexity or financial and time efforts or because of a lack of reliability in the rough surrounding of industrial production [19]. Therefore, the motor current-based grinding chatter detection system proposed in this study is of great industrial application value.

## 3 Theoretical background of chatter detection using servo feed motor current

A lot of research work indicated that cutting torque is a perfect signal for chatter detection [2, 25, 26]. However, the application of cutting torque transducer is constrained by some factors like transducer setup, mechanical compatibility, and cost. Therefore, researchers tried to acquire the equivalent cutting torque using other indirect methods, within which the equivalent conversion of motor current signals is a considerable and successful method.

Young [4] constructed a dynamical model of machine tool feed drive system to determine the relationship between the cutting force, motor current, and motor rotation. The motor servo drive system is composed of three parts, the position loop, the velocity loop, and the current loop. The torque equation of the feed drive system can be derived as follows:

$$T_{\mathrm{m}} = J_{\mathrm{m}}\frac{\mathrm{dw}}{\mathrm{dt}} + T_{\mathrm{d}} = J_{\mathrm{m}}\frac{\mathrm{dw}}{\mathrm{dt}} + T_{\mathrm{cutting\ \ force}} + T_{\mathrm{friction}} = K_{\mathrm{t}}I_{\mathrm{q}} \quad (1)$$

where $T_m$ is the motor torque, $J_m$ is the equivalent inertia, $w$ is the angular velocity, $T_d$ is the disturbance torque, $K_t$ is the torque constant, and $I_q$ is the converted equivalent DC from the three-phase AC.

The worktable moves once the motor torque ($T_m$) overcomes the disturbance and table inertia. In the cutting process, the disturbance can be divided into frictional torque and the torque caused by cutting force. During the steady cutting process, the effects of frictional torque and inertia torque can be neglected. Therefore, the cutting torque is proportional to the motor current $I_q$ approximately.

The three-phase AC can be converted into DC using a DQ transformation, whereas the root mean square (rms) method is more often used in industrial conditions [5]. In the steady state, the rms current value multiplied by √3 is the $Q$-axis current ($I_q$). We used the rms value as the equivalent DC to calculate the motor torque. The formula is

$$I_{\mathrm{rms}} = \sqrt{\frac{1}{3}\left(I_{\mathrm{u}}^2 + I_{\mathrm{v}}^2 + I_{\mathrm{w}}^2\right)} \quad (2)$$

Therefore, by measuring the motor three-phase currents and converting them into DC, the equivalent cutting torque can be acquired.

Moreover, along with the improvement of modern NC machine tool servo drive system, the precision, sensitivity, and frequency response of the NC system all reach a high level. In some advanced and complicated machining processes, such as gear grinding [27] and curved surface milling, synchronous movements of multiple axes are required. Mostly, the movement of the workpiece axis is constrained by the synchronous relationship with other active moving axis. For example, in this study, during the gear generating grinding process, the theoretical angular velocity of the workpiece axis is decided by tracking and sampling the movement of the grinding wheel axis and two feed axes, then closed loop controlled by the NC system. When chatter occurs, the machine tool system, including the workpiece axis, grinding wheel axis, and feed axes, all will vibrate with the chatter frequency. And the NC servo system will respond to this vibration, track, and compensate to the chatter of these axes automatically. Therefore, components corresponding to the chatter frequency are contained in the workpiece axis motor currents.

As stated above, on the one hand, equivalent cutting torque can be acquired from the motor currents. On the other hand, components corresponding to the chatter frequency are injected actively into the workpiece axis motor currents when chatter occurs. Therefore, chatter can be detected effectively by analyzing the servo feed motor current.

## 4 Chatter frequency band identification and feature extraction based on WPT

The first feature in the process of chatter generating is that the vibration energy transfers from high frequency to low frequency, and the frequency band becomes narrow at the same time. Then, in the time domain, the vibration amplitude begins to grow significantly [28]. Therefore, compared with time domain monitoring, frequency domain monitoring is more fundamental and important.

Wavelet packet transform decomposes signal in the frequency domain as a decomposition tree. Compared with DWT, WPT can provide a more elaborate signal analysis. It decomposes the signal at the whole frequency band; therefore, the higher frequency resolution can be obtained [29]. As an illustration, the three-level WPT decomposition process is displayed in Fig. 1. A signal $x(t)$ is decomposed by WPT, and the wavelet packet signal $x_{i,j}$ is produced, where $x_{i,j}$ denotes the $j$th frequency band signal at level $i$ ($j=1,2,\ldots,J$, where $J$ is the number of decomposed wavelet packets and equals $2^i$, and $i=1,2,\ldots,I$, where $I$ is the decomposition level). The frequency bandwidth of $x_{i,j}$ is denoted as $[(j--1)2^{-i}f_N, j2^{-i}f_N]$, where $f_N$ is the upper limit of the signal frequency covered by $x(t)$.

The signal is decomposed into independent frequency band with no redundant, exhaustive, and orthogonal characteristic; thus, the SNR of the feature signal is improved [30]. The energy of every single frequency band reveals different status information during the machine running process and can be used as an important criterion for machine dynamic analysis, monitoring, and diagnosis [31]. With the help of WPT analysis, we can observe the energy change of every frequency band completely, realizing frequency domain monitoring of the machining process.

To detect chatter at its early stage, the feature frequency band signal of chatter should be focused on. This signal may have remarkable characteristics of chatter as many interfering information has already been filtered. When chatter develops, the energy of the frequency band where chatter locates is bound to increase. Therefore, by monitoring the energy change of all frequency bands, we can identify the chatter frequency band analytically and precisely. By tracking and monitoring the feature frequency band specifically, the detection of weak chatter in its early stage can be realized.

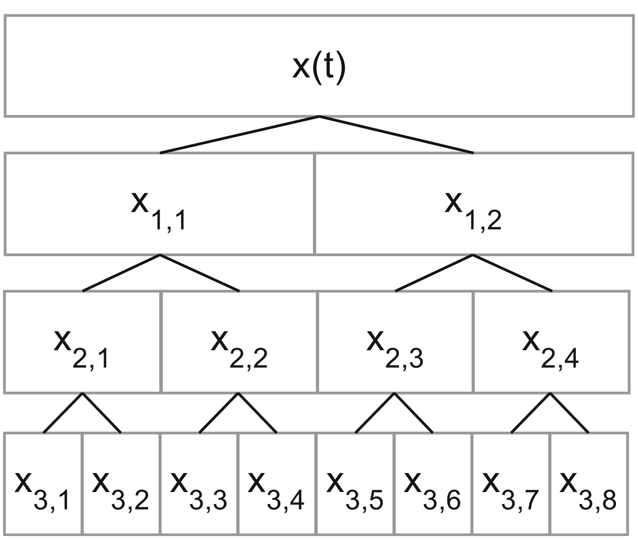



**Fig. 1** Three-level WPT decomposition process

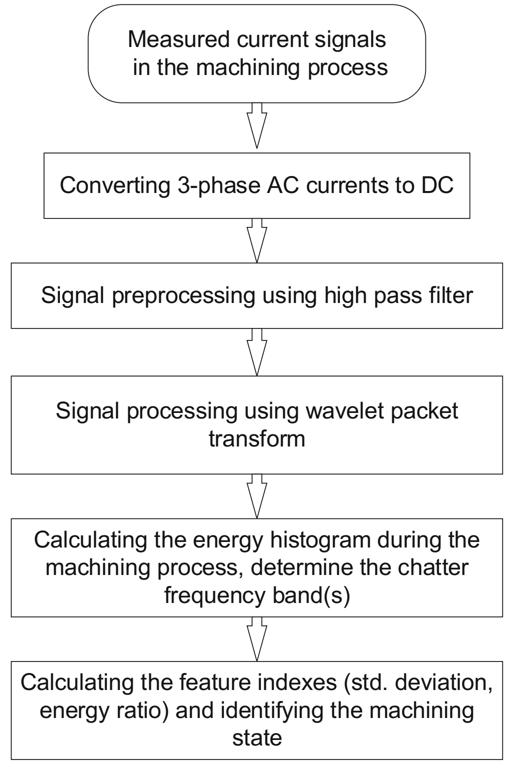



**Fig. 2** Framework of the proposed chatter detection scheme

The implementation of early chatter identification is to detect the trend of chatter in the transition state based on relevant features. Two kinds of chatter features should be considered: (1) the increase of the signal amplitude in time domain and (2) the energy transfer in frequency domain. Standard deviation of the signal can reflect changes of the signal amplitude in time domain, so that it can be chosen as a feature index. Energy ratio of each wavelet packet clearly demonstrates the developing process in frequency domain in the course of chatter emerging and reflects the fundamental cause of chatter;

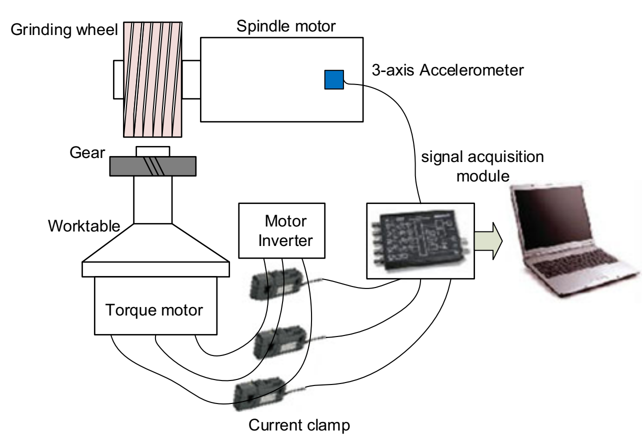



**Fig. 3** Schematic diagram of the experimental setup


**Fig. 4** Setup of the workpiece and sensor

thus, it can be chosen as another feature index. The energy ratio can be calculated with the following steps.

$$E_i = \sum_{n=1}^{N} |c_i(n)|^2 \tag{3}$$

$$E = \sum E_i \tag{4}$$

$$r_i = \frac{E_i}{E} \tag{5}$$

where $c_i$ is the reconstructed signal of the $i^{\text{th}}$ wavelet packet, $n$ is the coefficient index, and $r_i$ is the energy ratio of the $i$th wavelet packet.

The framework of the proposed chatter detection scheme is illustrated in Fig. 2, which contains the following main steps:

(1) Sample the three-phase AC signals and convert them into equivalent DC.
(2) Filter the DC signal with a high-pass filter to remove the low frequency trend.
(3) Decompose and reconstruct the DC signal into a set of multiple frequency bands using WPT.

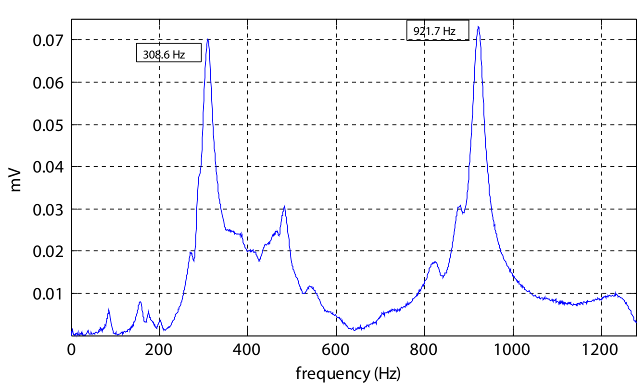



**Fig. 5** Frequency response function of the grinding wheel spindle

**Table 1** Experimental conditions

| Machining stage | Grinding wheel speed (rpm) | Grinding feed (mm/stroke) |
|---|---|---|
| Rough machining (four strokes) | 4000 | 0.12 |
| Semi-finish machining (one stroke) | 4000 | 0.06 |
| Finish machining (one stroke) | 2000 | 0.03 |

(4) Calculate the energy ratio of every single frequency band during the machining process and plot the energy histogram.
(5) Identify the feature frequency band by observing the energy histogram (the variation trend of which follows the machining process changes).
(6) Calculate the feature indexes of the feature frequency band signal and identify the machining state.

## 5 Experimental setup

The experiments were performed on a worm wheel gear grinding machine, which uses a permanent magnet synchronous motor (PMSM) supplied by three-phase AC to drive the worktable. The scheme diagram of the experimental setup is illustrated in Fig. 3. Three current sensors (HIOKI 9278 Universal Clamp ON CT, Japan), which have a bandwidth of 100 kHz, were used to measure the servo feed motor current. A three-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°. The clamping of workpiece and setup of acceleration sensor are shown in Fig. 4. A high-speed signal acquisition system (DT 9738B, dynamic signal acquisition modules) was used to collect acceleration signal and current signal synchronously. So, it is favorable for comparative analysis of acceleration signals and current signals.

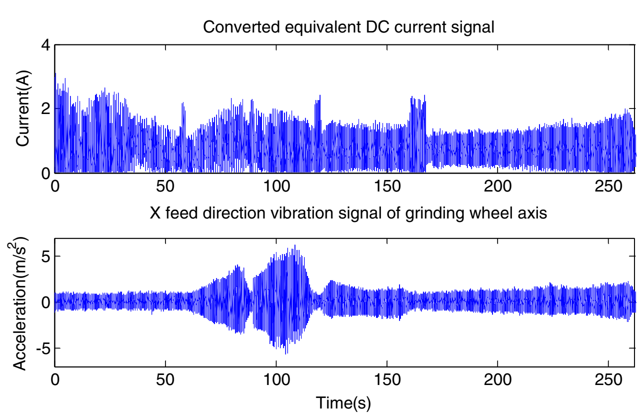



**Fig. 6** Converted equivalent DC signal and vibration signal ($X$ direction)

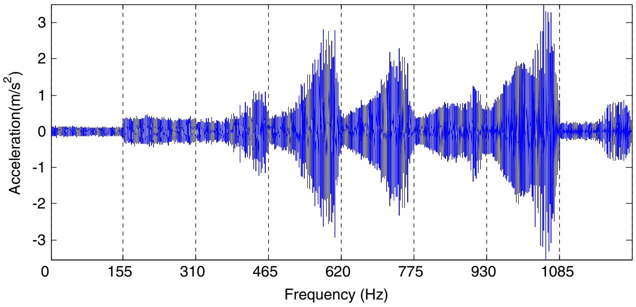



**Fig. 7** Reconstructed signals of eight wavelet packets in the third stroke

The grinding wheel spindle dynamics was obtained through impact hammer test. Figure 5 shows the measured frequency response function (FRF) without wheel contact. It can be seen that there are two dominant modes, whose natural frequency is 308.6 and 921.7 Hz, respectively.

Before grinding test, all the gears were ground once to eliminate the thermal distortion. The whole machining process is composed of three stages: rough machining, semi-finish machining, and finish machining. The grinding wheel traveled six strokes along the gear axis, namely every gear flank surface would be ground six times. Oil-based coolant was used throughout the machining process. Table 1 lists the experimental conditions of the grinding process.

## 6 Experimental results and discussion

figure 6 displays the converted DC motor current signal and X feed direction vibration signal of the grinding wheel axis collected during the whole machining process.

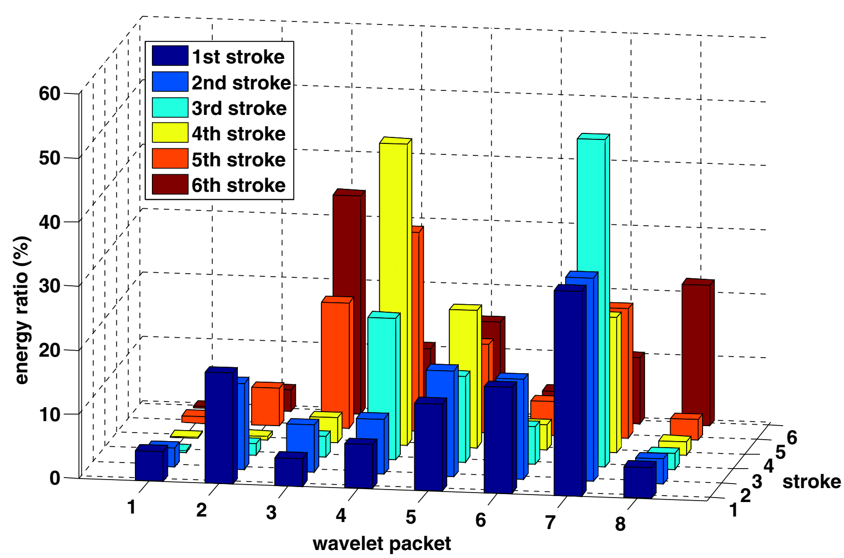
Along with the grinding process, chatter experiences the process of generation and development. In every single stroke, the vibration amplitude increases along with chatter development. Between adjacent strokes, the regenerative effect of the grinding wheel aggravates arising from the grinding wheel wear, resulting in the gradual increase of chatter amplitude. However, constrained by the inner feedback mechanism of chatter, the vibration amplitude will not keep on increasing without limit. Instead, the amplitude is susceptible to machining conditions, like grinding wheel speed, grinding feed, and grinding wheel topography. Therefore, the current signal was divided into six parts according to the grinding strokes and analyzed independently.

When applying WPT, the parameters needed to be considered are the decomposition level and the wavelet basis. If the decomposition level is too small, the frequency band of the wavelet packet will be too wide, which means more irrelevant frequency components to chatter will be included, and then decrease the SNR and the sensitivity of chatter features. On the contrary, if the decomposition level is too large, the frequency band will be very narrow, which makes the feature information of chatter cannot be concentrated in a single frequency band and the identification of chatter frequency band gets complex. For the selection of wavelet basis, Daubechies wavelets have many good characteristics for the application of feature extraction, like compactly supported, orthonormal, the highest number of vanishing moments for a given support width. When the order gets larger, the cutoff characteristic of the wavelet filter is closer to that of an ideal filter, on the cost of longer calculation time, however. After comparing and balancing, the vibration signal was decomposed to the third level using Daubechies wavelet db10, acquiring eight reconstructed signals. Figure 7 shows the waveforms of the reconstructed signals in the third stroke.

To calculate the energy ratio of every wavelet packet, we will obtain the energy ratio histogram of eight frequency bands in six strokes as shown in Fig. 8.

During the rough machining stage, along with the grinding process development, grinding wheel wear aggravated and the

**Fig. 8** Energy ratio histogram of vibration signal



regenerative effect enhanced; thus, chatter amplitude increased gradually. During the semi-finish machining stage, the grinding wheel speed was the same as before, while the grinding feed decreased, leading to the decrease of grinding force and the chatter amplitude as well. During the finish machining process, both the grinding wheel speed and grinding feed decreased; at the same time, new grinding wheel thread was used to impair the negative effect caused by grinding wheel wear. All these factors gave rise to the substantial decrease of grinding force and thus chatter amplitude.

According to the qualitative description above, the fourth frequency band in Fig. 8 whose frequency interval is 465–620 Hz (Fig. 7) is found to obey this variation trend, while the left frequency bands show apparent difference. Furthermore, stability analysis by solving the system characteristic equations shows that the machine structure will be excited in the range of its dominant natural frequencies and the chatter frequency is always higher than the natural frequency of the mechanical system [19]. The fourth frequency band is in accordance with this conclusion compared with the results of the hammer test shown in Fig. 5. Thus, the fourth frequency band is just the feature frequency band where the majority of chatter information locates. This is confirmed further by the time-frequency distribution of the vibration signal (Fig. 9).

As shown in Fig. 9, there is still some leakage of the chatter energy in the adjacent frequency bands (the third and fifth) and there is another chatter frequency band (the seventh); this explains the dramatic energy ratio increase of it at the third stroke (Fig. 8) when chatter emerged. At the fifth stroke, the grinding feed reduced, the energy in the fourth frequency band decreased, while the 400 Hz frequency component in the third frequency band was large in amplitude; therefore, the energy ratio of the third frequency band increased a lot. At the sixth stroke, both grinding wheel speed and grinding feed were reduced; new interference component with large amplitude appeared at the eighth frequency band causing the sudden

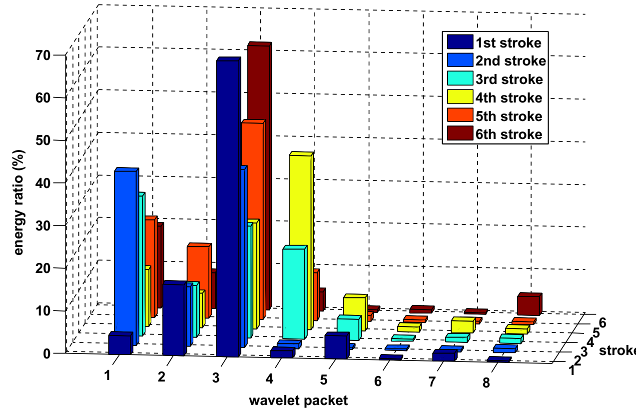
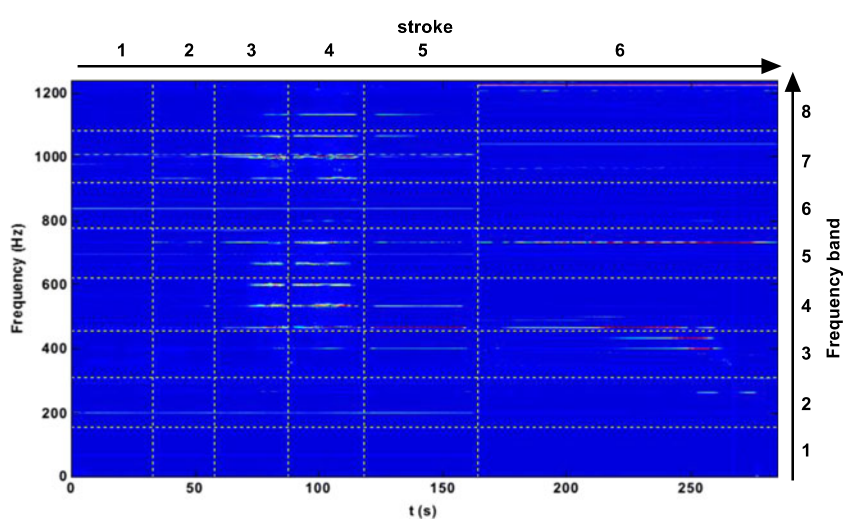



**Fig. 10** Energy ratio histogram of DC signal

energy ratio increase of it. The decrease of the grinding wheel speed gave rise to the decrease of the frequency interval of chatter harmonics and the downshift of chatter frequency band. Therefore, the energy ratio of the third frequency band grew up at the sixth stroke. This problem will be the research direction for future works. To summarize, despite the interference from the energy ratio changes of other frequency bands, the dominant chatter information is covered in the fourth frequency band before the grinding wheel speed changed and the variation trend of chatter state can be precisely revealed by the fourth frequency band.

The result of applying the same processing method to the current signal is shown in Fig. 10. The similar variation trend can be observed in the fourth frequency band, except that the energy ratio of the first stroke is a little higher than the second stroke, which is not consistent with the hypothesis. This may be caused by the interference error of WPT based on Mallat algorithm [32]. However, basically, the variation trend was consilient with that of vibration signal, which meant the chatter information was also revealed in the current signal and the fourth frequency band was the feature frequency band.

**Fig. 9** Time-frequency distribution of the vibration signal



The time domain waveforms and feature curves of the fourth frequency band current signal in all strokes are shown sequentially in Fig. 11.

The big waves in the first stroke may come from the non-uniform machining stock of the gear, since it was a new workblank. During the second stroke, the grinding process become stable, the time domain waveform and feature curves are all stationary, and the energy ratios is low. During the third stroke, chatter begins to occur and develop. The waveform and feature curves all grow observably, and the energy ratio rises to about 50 % rapidly. During the fourth stroke, chatter keeps increasing slightly on the basis of a large amplitude. Constrained by the numerous nonlinear factors, chatter amplitude does not keep on increasing unlimitedly, but stabilizes within a range after a while. The energy ratio of the fourth frequency band is the highest among all frequency bands and keeps a value between 40 and 60 % basically. In the fifth stroke, chatter keeps decreasing gradually. At the beginning of the sixth stroke, chatter still increases slightly, but the amplitude and energy ratio are both quite small and decrease gradually in the end.

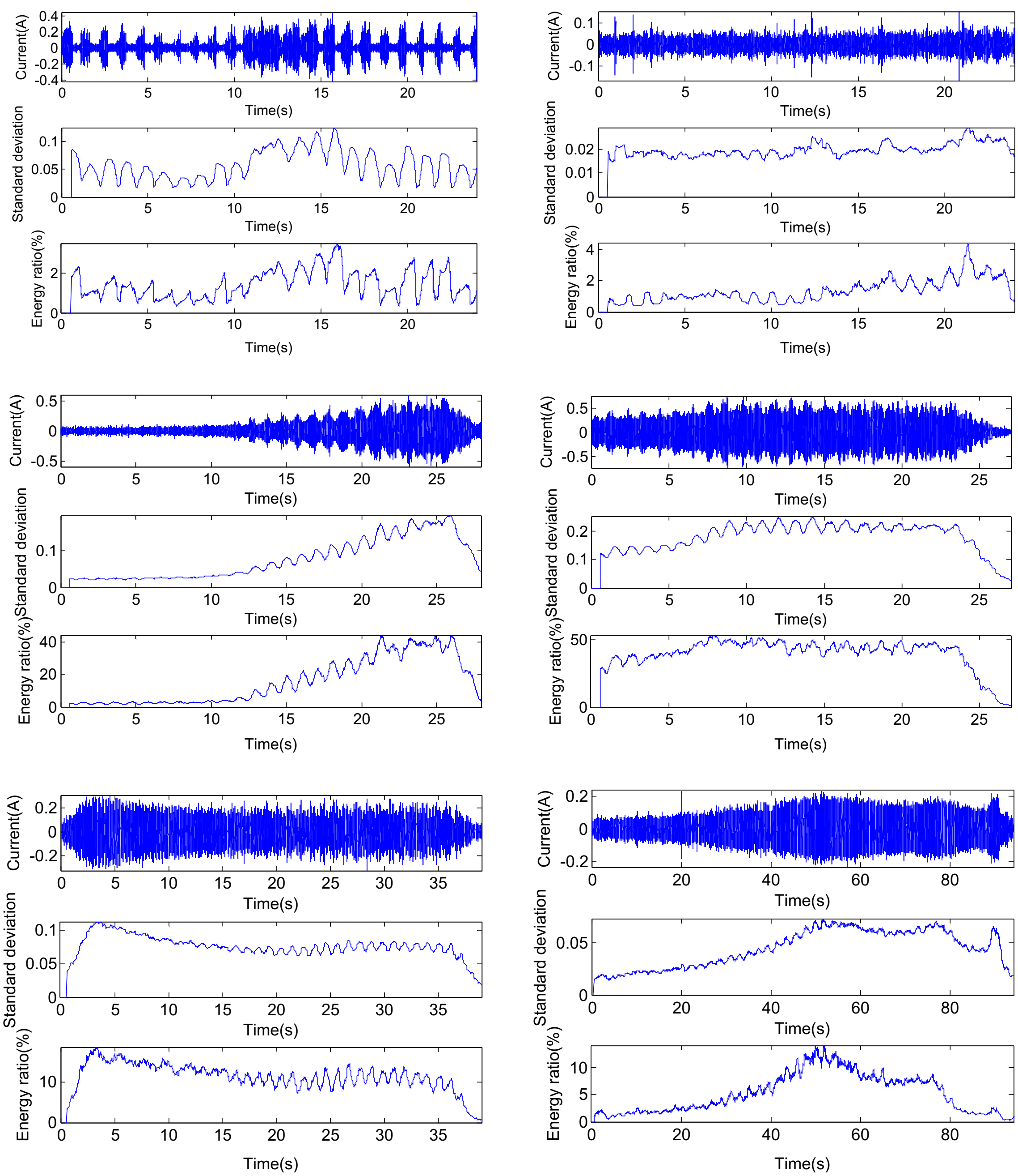



**Fig. 11** Waveforms and feature curves of the feature frequency band current signal

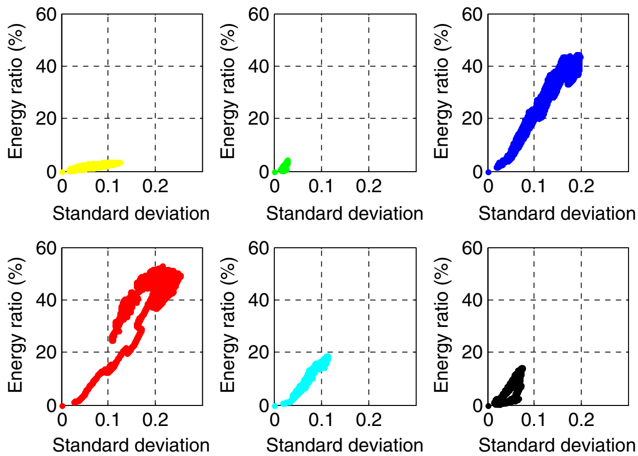



**Fig. 12** Machining state classification based on the two chatter features

Combining these two chatter features, the state of the grinding process can be classified as shown in Fig. 12. With a threshold value of 0.1 for standard deviation and 20 % for energy ratio, chatter can be detected reliably in industrial application. When both thresholds are exceeded, it can be judged that chatter happens. The chatter state classification of the sixth stroke may have some deviation because of the downshift of the chatter frequency band.

The waveforms of vibration signal in the fourth frequency band of all strokes are shown in Fig. 13. In every stage of the grinding process, the current signal and vibration signal have shown very coincident variation trend. This phenomenon was verified by a series of experiments and the inevitability was demonstrated. This result verified the correctness of the theory of chatter detection by using servo feed motor current.

To illustrate the early chatter detection property of this technique, the DC signal of the third stroke, during which chatter appeared, was analyzed without feature signature

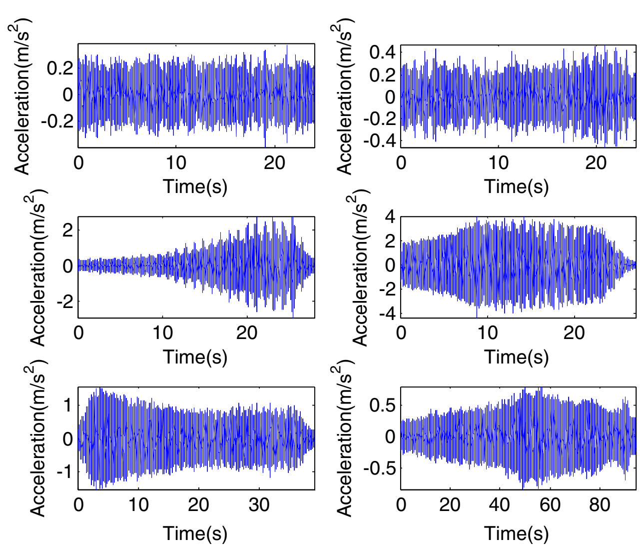



**Fig. 13** Waveforms of the feature frequency band vibration signal

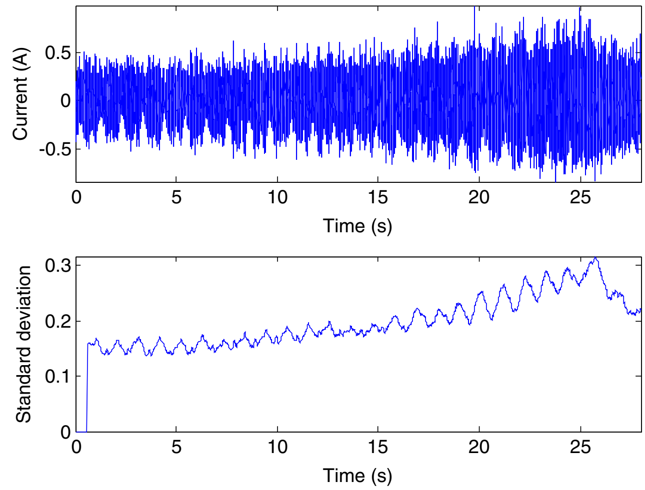



**Fig. 14** Waveform and std deviation curve of the third stroke DC after filtering

extraction. The time domain waveform after high-pass filtering and its std deviation curve are shown in Fig. 14.

Compared with Fig. 14, the onset of chatter is much clearly revealed in the waveform and feature curves of the third stroke in Fig. 11. The threshold to detect the occurrence of chatter in Fig. 11 is much lower than that in Fig. 14, which enhances the early chatter detection ability. These properties will bring much more efficiency, accuracy, and time advantage in detecting chatter.

## 7 Conclusions and future works

A convenient and reliable technique to detect early chatter in gear grinding process based on servo feed motor current and wavelet packet transform was presented in this study. WPT was used to monitor the energy change in the frequency domain and identify the chatter frequency band analytically, the result of which was confirmed by the impact hammer test. Standard deviation and energy ratio of the feature frequency band signal were chosen as the indexes of chatter monitoring. Combining these two chatter features, the state of the grinding process could be classified and chatter could be detected reliably in industrial application with proper thresholds. Acceleration signals of the machine tool were used as a reference to compare with the results from current signals. In every stage of the grinding process, the feature frequency band signals of current and vibration signal have shown very coincident variation trend. Both theoretical analysis and experimental results manifested the feasibility and efficiency of the proposed chatter detection method.

Because of the inherent characteristics of grinding chatter, chatter frequency band may shift with the grinding wheel speed. This would cause some deviation for the chatter state classification when applying the proposed method. Future works should be done to solve this problem.

**Acknowledgments** The work is supported by the National Natural Science Foundation of China (Grant No. 51421004, 51125022) and the Fundamental Research Funds for the Central Universities of China (Grant No. CXTD2014001) which are highly appreciated by the authors.

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