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Feature Enhancement Method for Drilling Vibration Signals by Using Wavelet Packet Multi-band Spectral Subtraction

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To address the difficulty in extracting the features of vibration signals under intense background noise, a new method is proposed based on wavelet packet multi-band spectral subtraction to intensify vibration signal features in drilling processing. First, it is assumed that the spindle vibration signal of machine idling and the vibration signal caused when the tool cuts the workpiece are independent of each other, and the machine's idling signal is perceived as the 'additive noise' of the monitoring signal in light of the spectral subtraction principles. Secondly, in line with the characteristics of vibration signals in the drilling process, the 'additive noise' and monitoring signal are split into multiple frequency bands via wavelet packet decomposition. Eventually, spectral subtraction is performed independently in each band, and the vibration signals are reconstructed. The simulations and experimental results indicate that the new method should effectively eliminate the impact of environmental noise on the process of feature extraction to intensify the features of the monitoring signal.
Keywords: vibration signal, feature intensification, wavelet packet decomposition, spectral subtraction

Highlights
- *A new method is proposed based on wavelet packet multi-band spectral subtraction to intensify vibration signal features in drilling processing.*
- *We have addressed the difficulty in extracting the weak features of vibration signals under intense background noise.*
- *Compared with the traditional threshold de-noising method, the problem of threshold selection can be avoided.*

0 INTRODUCTION

According to the change in contact position between the drill edge and the workpiece, drilling machining is classified into three stages, namely, drilling guide, drilling, and drilling out [1]. In the monitoring of drilling, the signal features corresponding to the previous stage are extracted, and the mapping model is established to monitor the drilling process [2]. This can lay a theoretical foundation for realizing high-precision drilling quality analysis; the premise is how to achieve feature enhancement by implementing signal de-noising effectively in a complicated drilling environment.

As it is an advanced sensor-and-signal processing technology, a growing number of scholars have been extensively adopting various kinds of sensors to ascertain the drilling process and drilling quality. The monitoring and prediction of tool wear and breakage in drilling are mainly done indirectly through thrust force [3] to [5]. Ferreiro et al. [6] and [7] and Peña et al. [8] completed the burr monitoring by extracting the features from the spindle torque signal in the drilling process. Ramirez et al. [9] established a temperature model for the drilling tool and combined the cutting force signal and temperature signal characteristics to evaluate the surface quality of the drilled surface. Xiao et al. [10] via constructing a valuable indicator, i.e., the wavelet energy ratio around the natural frequency of boring bar vibration signal to monitor tool wear and surface finish quality for deep hole boring, developed a method to monitor and evaluate tool wear during drilling through the monitoring of vibration and acoustic emission signals [11] and [12]. It is well known that the key to achieving the quality monitoring of drilling is to extract abnormal features from the monitoring signals, but the signal features representing drilling quality are often very weak, so it is necessary to pre-process the signal to intensify its features. The above researches on abnormal state monitoring and diagnosis during the machining process can be divided into two classifications: extracting the evident features of monitoring signals to determine abnormal tool damage and drilling quality, and ascertaining the tool wear and the quality of drilling trends by anatomizing the overall monitoring signal. The results of these studies have good guidance significance to ensure high-precision drilling quality. However, they cannot predict or inform when and where tool breakage and quality is abnormal. Therefore, it is of great necessity to ascertain the feature extraction problem of the drilling process signal, establish a mapping model of the monitoring signal and the drilling process, and accurately identify the time and location of abnormal

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drilling process problems. Accordingly, the quality of high-precision drilling can be effectively protected.

From a theoretical perspective, when the relative contact position of the drill edge and workpiece changes, the monitoring signal occurs with varying degrees of mutation and forms the corresponding signal features. Compared to the features of the tool wear and the cutting system anomaly, the features of the monitoring signal are weak during drilling. In fact, when using the sensors to monitor the drilling process, the monitoring signal is commonly encompassed in a large section of the machine idling signal before the drill edge is cut into the workpiece; this section comprises the machine tool motor, transmission, electrical systems, and other noise.

In this work, we propose a method for the vibration signal by adopting wavelet packet multi-band spectral subtraction (WPMSS) to intensify the signal features during drilling. First, the machine tool idle signal is perceived as the additive noise of the monitoring signal. Then, the additive noise signal and monitoring signal are split into multiple sub-bands in each band by adopting wavelet packet decomposition (WPD). Finally, spectral subtraction is performed independently in each band.

The use of WMPSS to analyse the drilling signal should first satisfy the condition that there is no correlation between the machine idle signal and the vibration source signal generated during the drilling process. Owing to the complexity of the drilling process, it is determined that the correlation between the machine idle signal and the vibration source signal during the drilling process cannot be proved by a specific mathematical formula, and the correlation between the two cannot be described quantitatively. Therefore, we can only qualitatively and experimentally determine a certain number of assumptions, which are based on the following points:

(1) The drilling monitoring signal in the experiment contains idle and drilling process information. The drilling idle phase contains almost all of the environmental noise and vibration information of the machine tool. Therefore, the machine idle signal can be used as the processing disturbance signal of the drilling process. That is, it is possible to use it as 'additive noise' in spectral subtraction;
(2) It can be discovered from the experimental study that the spectrum of the idle signal of the machine tool has not changed from idle transition to completion of the drilling process, which indicates that they are independent of each other between the machine idle signal and the vibration source signal generated during the drilling process, that is, both are irrelevant.
(3) Through a large number of experimental studies, it is found that there is a certain positive effect on feature retention and the signal-to-noise ratio (SNR) after spectrum subtraction. Thus, we think that spectral subtraction is effective and applicable. In addition, this proves that it satisfies one of the preconditions for spectral subtraction, that is, noise and source signals are independent of each other.

WPMSS is a combination of wavelet packet and spectral subtraction. In some respects, spectral subtraction has a better de-noising performance than the threshold de-noising and filtering methods do [13], which avoids the difficulties of threshold selection and filtering of weak features, since spectral subtraction practically has little effect on the useful signal components, i.e. the weak features are not ignored. Simultaneously, the actual drilling vibration signal contains many non-stationary components related to the tool. However, the traditional power spectrum analysis is a description of the overall statistical law of the signal and does not have the capability of non-stationary signal analysis. Therefore, WPD is used to avoid these disadvantages. In addition, we find that the noise signal band is distributed over a wide frequency band in the drilling experiment. The power spectrum has a large random variation range, and the maximum and minimum values often differ by several orders of magnitude in the frequency domain. When classical spectrum subtraction is used, a large part of the residual noise components are generated, which appears as a random peak on the spectrum and has a great influence on feature extraction. Thus, the wavelet packet is used to decompose the signal into different frequency bands, and then spectral subtraction processing is performed using different spectral subtraction parameters in each frequency band to extract features conveniently [14]. Therefore, we should focus on how to obtain accurate spectral estimation of noise signals in drilling vibration signals with a frequency range of 0 kHz to 10 kHz.

This paper is organized as follows. The principle of the improved spectral subtraction is explained in section 1, and the simulation analyses for the previous theoretical model is given in section 2. The experiment for feature intensification of vibration signals in the drilling process by using the proposed method is presented in section 3. Conclusions are finally addressed in section 4.

1 METHODS

1.1 Classical Spectral Subtraction

Spectral subtraction is the most commonly used method in speech-sound intensification. The principle of classical spectral subtraction is exhibited in Fig. 1. Classical spectral subtraction is based on the statistical stability of noise and the characteristic that additive noise is not correlated to speech sound. In the frequency domain, the power spectrum of the noisy signal is subtracted from that of the noise signal to estimate the power spectrum of the clean signal. Then, the amplitude of the clean signal is estimated after the square root is taken. Next, the phase of the clean signal is estimated as the phase of the processed signal, and the inverse Fourier transform can be adapted to obtain the intensified clean signal in the time domain [15].

The algorithm implementation flow is as follows:

Suppose the clean signal containing the noise is:

$$x(i) = s(i) + n(i), \tag{1}$$

where $s(i)$ and $n(i)$ are the clean and noise signals, respectively. Transforming Eq. (1) from the time domain to the frequency domain using the Fourier transform:

$$X_K = S_K + N_K\,. \tag{2}$$

Thus, $|X_K|^2$ is written as:

$$|X_K|^2 = |S_K|^2 + |N_K|^2 + S_K \cdot N_K^* + S_K^* \cdot N_K\,. \tag{3}$$

Because $s(i)$ and $n(i)$ are independent of each other:

$$E|X_K|^2 = E|S_K|^2 + E|N_K|^2\,. \tag{4}$$

In fact, most of the noise signals are unstable, and thus the signal is framed before spectral subtraction to make the signals in each window length meet the short-time stability. Thus, a more accurate spectrum estimation can be attained.

For a short-term stationary signal in a sub-frame:

$$|Y_K|^2 = |S_K|^2 + \lambda_n(k)\,, \tag{5}$$

where $\lambda_n(k)$ is the statistical average of 'additive noise', and the spectral estimation value of the clean signal can be approximated by:

$$\left|\hat{S}_k\right| = \left[\left|X_K\right|^2 - \left|N_K\right|^2\right]^{\frac{1}{2}}, \tag{6}$$

where $\left|\hat{S}_k\right|$ and $\left|X_K\right|$ are the spectral estimates of the clean and noisy speech signal, respectively. By substituting the clean signal spectrum estimation $\left|\hat{S}_K\right|$ into the signal phase $\angle X(K)$, the time domain signal $\left|\hat{S}_K\right|$ of each window clean is attained by the inverse Fourier transform as follows:

$$\hat{s}(k) = IFFT\left[\left|\hat{S}_K\right| \times \exp\left(\angle X(K)\right)\right], \tag{7}$$

where $IFFT$ is the inverse Fourier transform and $\angle X(K)$ the phase spectrum of the noisy speech signal. Then, by using a data window and overlapping the data between data segments nearby and eliminating the window function gain, an accurate clean $\hat{s}(i)$ is eventually determined.

It can be found from the above algorithm principle that the accurate estimation of the noise and

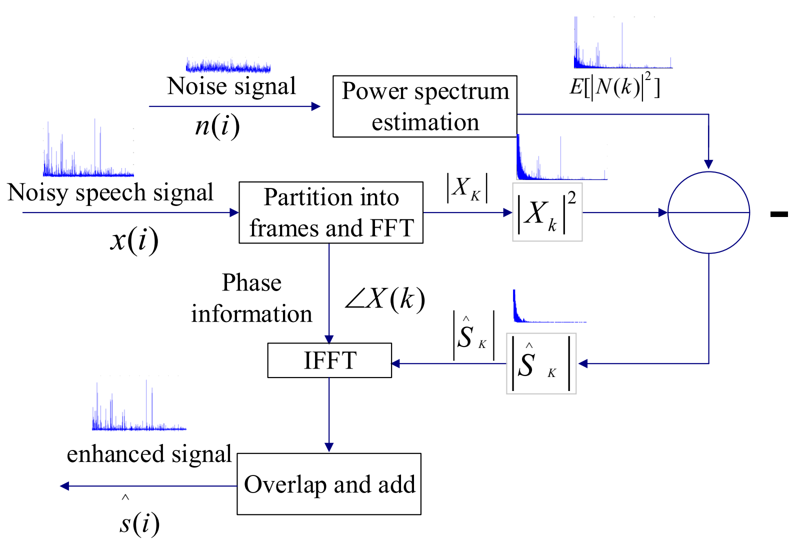

Fig. 1. *Principle diagram of the classical spectral subtraction*

noisy speech signal spectrum is the key to improving the spectral subtraction intensification signal features.

1.2 Improvement of Spectral Subtraction

Because the noise mostly does not affect the speech signal uniformly over the entire spectrum, Kamath and Loizou proposed the multi-band spectral subtraction method [14], which uses different spectral subtraction factors in different frequency bands and achieves good results. In fact, traditional spectral subtraction mainly applies to speech signals with a frequency range of 160 Hz to 1280 Hz and usually uses a fixed frame length of 256 or 512 sampling points to process the signals. However, for the drilling vibration signal with the frequency range of 0 kHz to 10 kHz, the uniform frame length obviously cannot satisfy the short-term stationarity in the high-frequency part of the signal and the accurate estimation of the signal spectrum in the low-frequency part.

Therefore, to obtain the accurate estimation of noise in the whole frequency band, wavelet packet decomposition was used to divide the signal into multiple frequency bands, and then use different frame length to estimate the spectrum of the signal in the high and low frequency bands. In brief, the frame length is required to be geared towards the short-term stability of the signal in the frame, and the sampling period is less than the minimum frequency in the study. When adopting the wavelet packet sub-frequency method for the signal with a bandwidth of 10 kHz, the short-term stability of the signals can be optimized for different frequency bands, and the accuracy of the spectrum estimation is in line with the needs of the research. WPD can not only decompose the low-frequency part of the signal, but also decompose the high-frequency part. It is defined as follows [16]:

$$\begin{cases} \mu_{2n}(x) = \sum h_k \mu_n(2x-k) \\ \mu_{2n+1}(x) = \sum g_k \mu_n(2x-k), \end{cases} \tag{8}$$

where $h_k(n)$ and $g_k(n)$ are the quadrature mirror filters. In particular, when $n = 0$, Eq. (8) is written as follows:

$$\begin{cases} \mu_0(x) = \sum h_k \mu_0(2x-k) \\ \mu_1(x) = \sum g_k \mu_0(2x-k). \end{cases} \tag{9}$$

Eq. (9) is the two-scale equation of scale function $\mu_0(x)$ and wavelet function degree $\mu_1(x)$, respectively.

Following the hypothesis that the wavelet packet decomposed the signal into j layers, the j layer in the range of $0-f_{\max}$ frequency domain were split into $0-f_{\max}/2^j, f_{\max}/2^j-2f_{\max}/2^j, \ldots, (2^j-1)f_{\max}/2^j-f_{\max}$ with a total of 2^j parts. In addition, WPD can adaptively select the corresponding frequency band to gear into the signal spectrum in line with the signal characteristics and analysis requirements. On this basis, an appropriate frame length is selected for

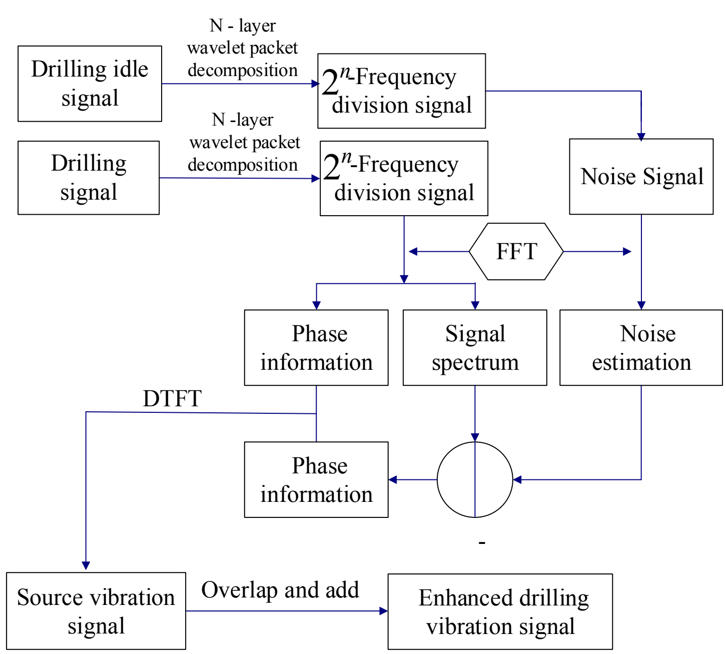

Fig. 2. *Principle diagram of the WPMSS*

spectral subtraction processing, which can facilitate the drilling signal intensification.

Therefore, this paper proposes a method in light of the spectral subtraction and WPD. Aiming at the drilling vibration signal with large bandwidth, first, it is proposed that the monitoring and noise signals are decomposed into multi-layers via WPD to attain the corresponding frequency band signal. Secondly, the frame length is selected in line with the sub-frequency of the noise signal in different frequency bands, and the average spectrum estimation value of each band signal is attained via a short-term Fourier transform. Next, the corresponding sub-frequency of the noise signal is processed by adopting spectral subtraction, and the sub-frequency de-noising signal is attained from the signals after spectral subtraction by inverse Fourier transform. Eventually, the signals of each frequency band after spectrum subtraction are superimposed and added to attain an intensified clean signal. The algorithm schematic diagram is as exhibited in Fig. 2.

2 SIMULATION ANALYSES

To verify the effectiveness of the proposed method for enhancing the features of drilling vibration signals, we verified its feasibility through simulation. The vibration signal during the drilling process mainly contains three components: the harmonic components related to machines, the modulation of some frequencies, and the aliasing of harmonic components. Therefore, the simulation signal of the drilling process with the sampling frequency f = 10 kHz is as follows:

$$x(t) = (1+\sin 5\pi t)\cdot\cos(50\pi t + 0.2\sin 10\pi t) + \sin 200\pi t + n(t), \tag{10}$$

where $n(t)$ represents random noise.

The signal is processed using classical spectral subtraction and WPMSS, and the three-layer wavelet

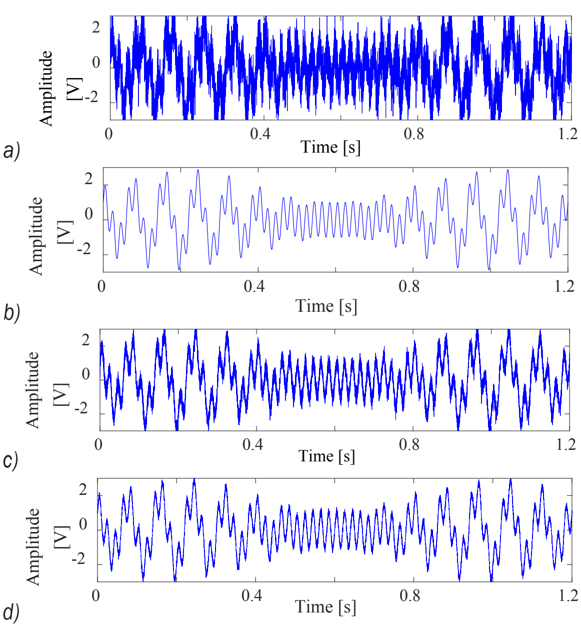

Fig. 3. *Time domain signal: a) clean signal with noise; b) clean signal; c) intensified signal by adoption of the classical spectral subtraction; and d) Intensified signal using wavelet packet subtraction*

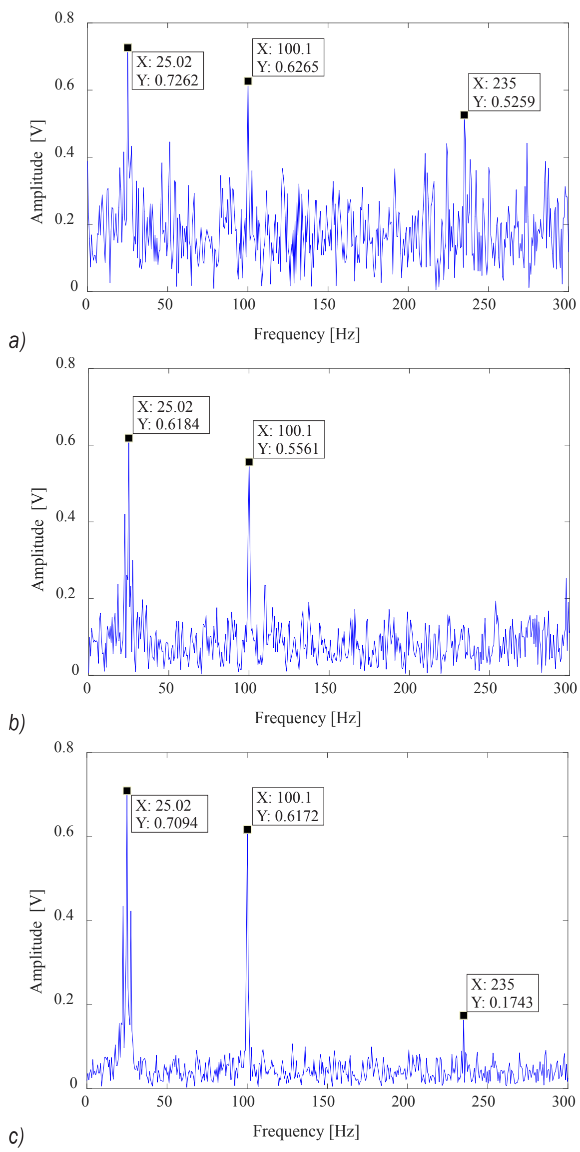

Fig. 4. *Spectra of the simulation signal: a) spectrum of the intensified signal by adoption of the classical spectral subtraction; b) spectrum of the intensified signal using wavelet de-noising; and c) spectrum of the intensified signal using WPMSS*

packet (db5) decomposition is used for frequency division processing of the simulation signal [17] to [20]. It is determined from Fig. 3 that the WPMSS in this study exceeds the classical spectral subtraction for the signals on the time domain waveform.

Fig. 4 shows the spectrum of the simulation signal, intensified signal by adopting the classical spectral subtraction, wavelet de-noising and WPMSS, respectively. Fig. 4a indicates that under the influence of strong noise, in addition to the inherent frequency feature of the simulation signal 25 Hz and 100 Hz, there are also many harmonic components with large amplitudes in the signal spectrum, such as 235 Hz after classical spectral subtraction, which significantly affects the signal feature extraction. From Fig. 4b, it can be concluded that there are still some small false feature components in the simulated signal spectrum that is processed by the wavelet method. It is indicated from Fig. 4c that the WPMSS can extract the relevant features of signal components in Eq. (10) effectively, and it also has a good effect on reducing noise.

In general, the SNR can be adopted to differentiate the effect exerted by signal analysis and processing [21]. The SNR is acquired as follows:

$$SNR\left(y_i\right)=10\times \lg\left[\frac{E\left|s_i\right|}{E\left\|y_i-s_i\right\|}\right](dB), \tag{11}$$

where $s(i)$ is the clean signal and $y(i)$ is the processed signal.

The SNR refers to the essential ratio of clean signal and noise, and the larger the SNR, the closer the processed signal to the clean signal. Table 1 indicates that the SNR of the simulation signal in Eq. (10) was processed with classical spectral subtraction, wavelet de-noising and WPMSS. In the simulation, it is evident that the trend of the SNR is exhibited in Table 1 by changing the clean and noise signals. This indicates that the WPMSS exceeds the classical spectral subtraction algorithm and wavelet de-noising in this study for the wide frequency band. Accordingly, the noise interference is not only eliminated, but the influence on the clean signal distortion is reduced.

Table 1. *SNR of the simulation signal*

Method	Spectrum subtraction	Wavelet de-noising	WPMSS
SNR	0.88	10.04	11.06

3 APPLICATION STUDY FOR FEATURE INTENSIFICATION WITH WPMSS IN DRILLING PROCESS

3.1 Drilling Experiments

In this study, the drilling process vibration signal is selected as the research object to ascertain the effect exerted by WPMSS to intensify the features of drilling process signals. The drilling experiment is exhibited in Fig. 5.

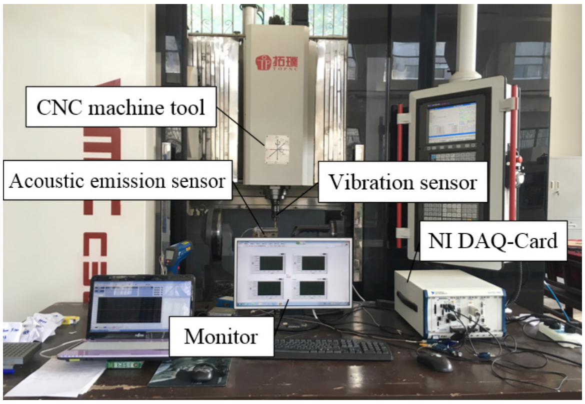

Fig. 5. *Hole-drilling experiment*

A Kistler8793A three-way acceleration vibration sensor and a Kistler8152B acoustic emission sensor are adopted as sensors in the experiment. The sensors are all installed on the spindle of the machine tool, and the Z-axis vibration signal is selected as the object. To minimize the influence of environmental noise on the signal, the drilling process is dry cutting, and the signal acquisition equipment used is the National Instruments Corporation's NI PXle-1082 chassis. In the course of drilling, the change in contact position between the drill edge and the workpiece evidently changes the high-frequency elastic stress wave signal because of the lattice dislocation slip inside the cutting deformation area material, especially when the drill edge is cut in and out of the workpiece. Therefore, the acoustic emission (AE) signal in the experiment is adopted primarily to comparatively ascertain the monitoring signal intensification effect by adopting WPMSS. The drilling processing equipment and process parameters are listed in Table 2.

First, we analyse the frequency spectrum of the drilling idling signal and the vibration signal. The spectral analysis (see Fig. 6) shows that the noise (drilling idling signal) and the noisy (drilling signal) spectrums are different in amplitude while they are occupying the same spectral band. It can be concluded that the conditions defined in the 4th paragraph of the introduction are satisfied so spectral subtraction can be applied to the drilling vibration signal. A similar analysis appears with the other researchers; they used a de-noising method by spectral subtraction to the detection of defects in ball bearings **[22]**.

Table 2. *Parameters used for experimental trials*

Description	Values (model)
Machine tool	VMC-C30
Material	Ti6Al4V
Hole diameter	8 mm
Spindle speed	600 rpm
Tool feed rate	0.5 mm/s
Sampling frequency	20 kHz

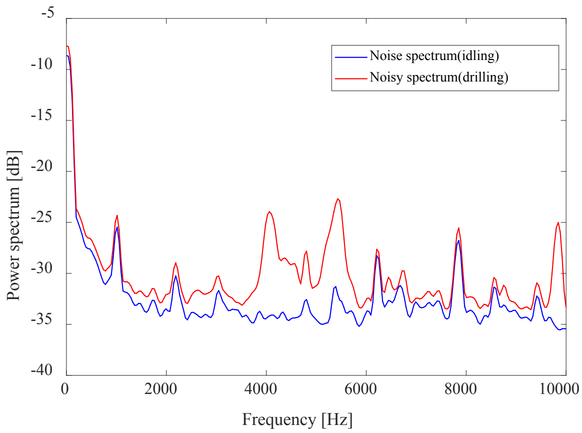

Fig. 6. *Spectral analysis of the noise (idling) and noisy (drilling) signal*

3.2 Comparison of Classical Spectrum Subtraction, Wavelet Packet and WPMSS with Drilling Signals

In the 24 holes of the aforementioned drilling, the monitoring signal of one hole (No. 3 borehole) is selected randomly as the research object.

It is indicated from Fig.7 that the eight different frequency band signals are attained by adopting a three-layer wavelet packet (db5) divider processing to divide the machine idle signal and the vibration signal. In addition, the appropriate frame length is determined by comparing the spectrum estimation of high frequency and low-frequency signals at different frame lengths through simulation and experiment, and the selection is based on ensuring the short-term stationarity of drilling signals in high-frequency frames and the spectrum estimation accuracy of signals in low-frequency frames. The frequency range and frame length subdivided by the wavelet packet of the vibration signal are listed in Table 3.

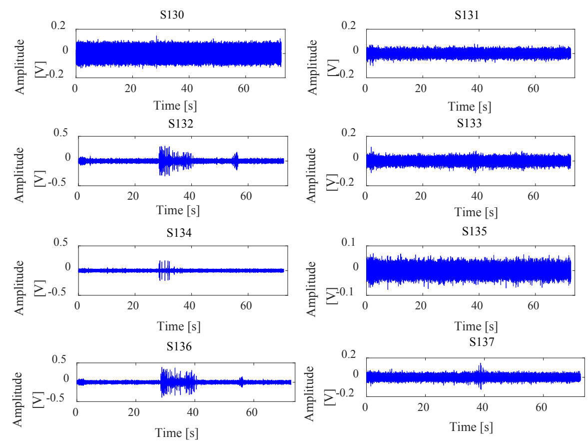

Fig. 7. *Time domain diagram of signal after WPD*

Table 3. *Wavelet packet frequency range and corresponding frame*

No.	Node	Frequency range [Hz]	Corresponding frame
1	[3,0]	0 to 1250	$2^{10}=1024$
2	[3,1]	1250 to 2500	$2^{9}=512$
3	[3,2]	2500 to 3750	$2^{9}=512$
4	[3,3]	3750 to 5000	$2^{8}=256$
5	[3,4]	5000 to 6250	$2^{8}=256$
6	[3,5]	6250 to 7500	$2^{7}=128$
7	[3,6]	7500 to 8750	$2^{7}=128$
8	[3,7]	8750 to 10000	$2^{7}=128$

3.3. Feature Intensification of Vibration Signal in the Drilling Process

The clean vibration signals of No. 3 are attained via classical spectrum subtraction, wavelet packet, and WPMSS, respectively, and the time-domain waveforms of the signal before and after the intensification are exhibited in Fig. 8. It can be seen from Fig. 8b that classical spectral subtraction has no obvious de-noising effect on the signal. This is mainly attributed to the classical spectral subtraction requiring the noise to be statistically stable throughout the speech segment; however, unlike white Gaussian noise, which has a flat spectrum, the spectrum of machine idle noise is not flat. Thus, the noise signal does not affect the speech signal uniformly over the whole signal. While Fig. 8c represents the drilling signal after processing by wavelet de-noising, the weak features can be easily filtered, such as the information of the drill edge drilled in and out of the workpiece, resulting in a loss of characteristic information. Fig. 8d shows that the interference of the noise in the intensified signal by adopting WPMSS is evidently eliminated. In particular, when the drill

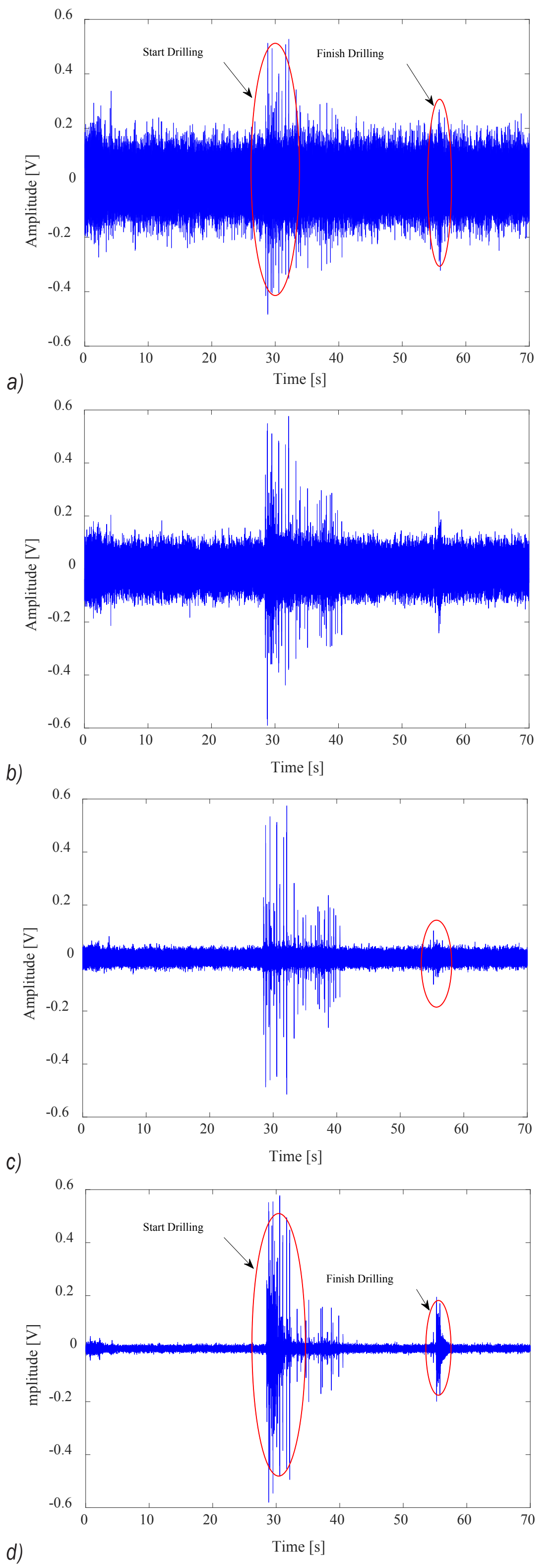

Fig. 8. *Time domain figure of vibration signals: a) original vibration signal of the drilling process; b) intensified signal through classical spectrum subtraction; c) intensified signal through wavelet packet; and d) intensified signal through WPMSS*

edge is drilled in and out of the workpiece, the abrupt feature of the vibration signal is intensified, and the instantaneous vibration texture at the time of drilling into the workpiece is also remarkably evident.

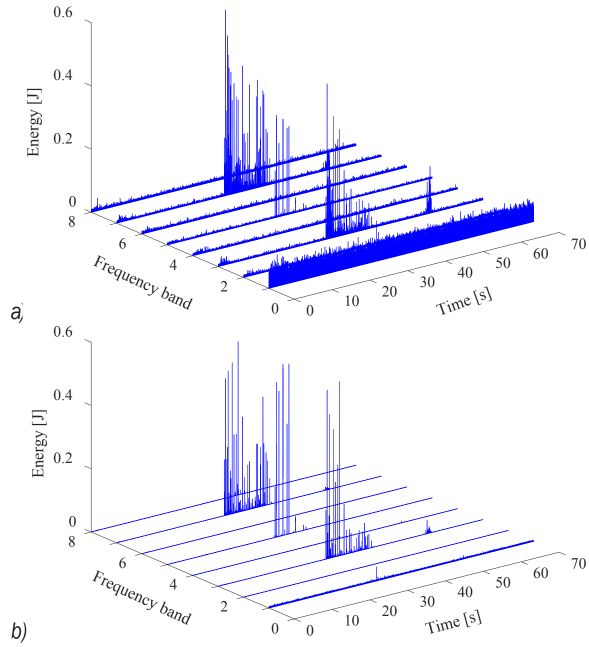

Fig. 9. *Energy distribution of 3D time-frequency domain in light of the WPD: a) wavelet packet energy distribution of noisy signal; and b) wavelet packet energy distribution of intensified signal*

In addition, when the vibration signal is decomposed into different frequency bands via the wavelet packet, the frequency band is confined by the energy and frequency. In this paper, the square of the WPD coefficient refers to the energy of the signal in the time domain [23]. From Fig. 9, it is evident that the energy distribution is basically the same, indicating that the method proposed in this paper has a certain inhibitory effect on noise.

3.4 The Energy Density Ratio (EDR) at the mutation before and after the signal was processed

The EDR of the signal mutation and stationary period can be adopted as an evaluation index to intensify the features of the vibration signal in the drilling process.

The formula for the energy density of the vibration signal can be expressed as:

$$E = \frac{1}{N}\sum_{i=1}^{N}\left[A(i)\right]^2, \tag{12}$$

where N is the signal sampling length and $A(i)$ is the amplitude of the signal. The energy density ratios of the signal mutation and stationary are equated as:

$$K = \frac{E_Z}{E_K}, \tag{13}$$

where E_Z and E_K are the energy densities at mutation and in the stationary period of the drilling vibration signal, respectively. For the same sampling length, the larger the K value, the more evident the mutation in the signal.

In this paper, ten of the 24 holes were randomly selected, and their energy density ratios were acquired in accordance with the drill edge instantaneously and before cutting into the workpiece. Fig. 10 presents the calculation results.

Table 4. *EDR of mutations and stability time*

Number of mutation times	Original signal	WPMSS
1	1.652	23.421
2	1.504	22.542
3	2.189	52.441
4	1.788	30.461
5	1.315	12.901
6	1.457	17.138
7	1.495	19.655
8	1.236	17.451
9	1.877	40.322
10	1.914	39.841

These data indicate that the energy ratio of the signal mutation and stationary period that is greater than ten times larger than those before the WPMSS algorithm was adopted to address the vibration signal.

3.5 Relationship between Vibration Signal Intensification and Acoustic Emission Signal during the Post-Drilling Process in Terms of Mapping

In the course of drilling, the AE signal is usually only sensitive to the stress wave generated by the micro-deformation of the material, which can effectively avoid the interference of low-frequency environmental noise. Therefore, the AE is adopted in this study to ascertain the effect exerted by WPMSS on the vibration monitoring signal of the drilling process. Fig. 10 illustrates the time-domain signal and the corresponding AE signals of No. 3 drill hole, which were not processed via WPMSS. The intensified signal and the corresponding AE signals in the time domain are exhibited in Fig. 11, the intensified signal of the workpiece that has just been drilled into and the corresponding AE signals in the time domain are exhibited in Fig. 12.

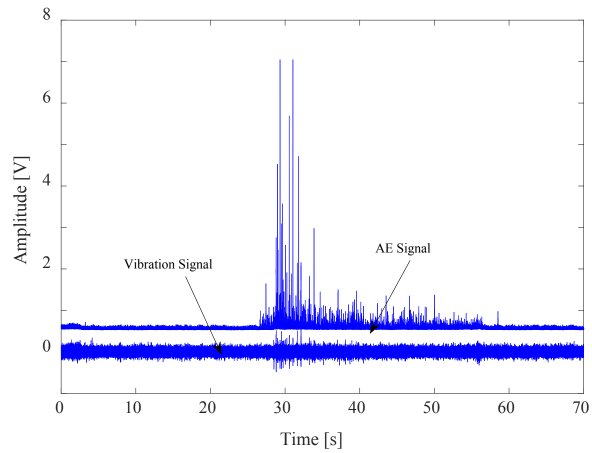

Fig. 10. *Time domain of untreated drilling process signals and the AE signal*

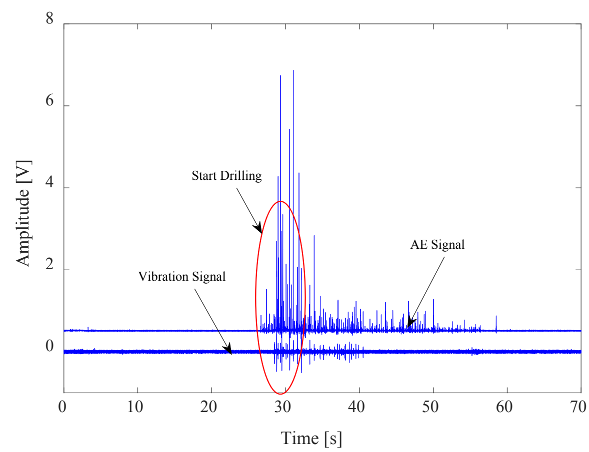

Fig. 11. *Time domain of the intensified signal drilling process and the AE signal*

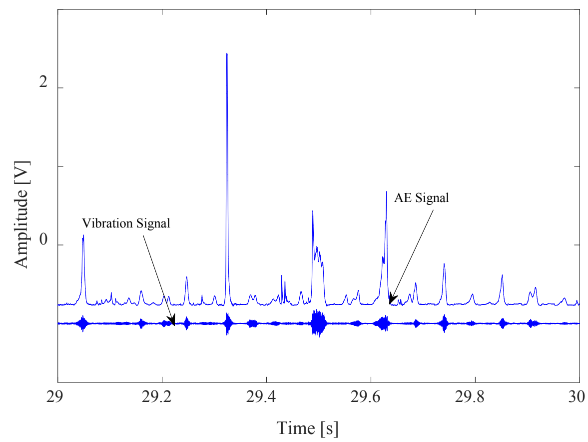

Fig. 12. *Time domain of the stage just drilled into intensified signal and the AE signal*

Fig. 12 is indicative of the processed vibration signal that is basically consistent with the abrupt change in the acoustic emission signal intensity. The results are indicative of the vibration signal of a drilling process that is perceived as 'additive noise' of the monitoring signal, and WPMSS can be adopted to eliminate the impact exerted by noise, including the machine operating signal.

4 DISCUSSION AND CONCLUSIONS

(1) The theoretical calculation and simulation analysis indicate that the 'additive noise' and the monitoring signal with a broad frequency band were split into multiple sub-bands with the same frequency range by adopting WPD, and thereupon the spectral subtraction and signal reconstruction eliminated the impact exerted by the 'additive noise' on the clean signal. Accordingly, the features of the monitoring signal can be effectively intensified.
(2) In line with the position change of the drill and workpiece, the monitoring signal was split into a machine idle signal and a drilling process signal. The machine idling signal acted as the 'additive noise'. On this basis, the 'spectral subtraction' was adopted to eliminate the impact exerted by environmental noise, comprising the machine idling signals on the monitoring signal of the drilling process, and the impact exerted by environmental noise, including machine idling signals, on the monitoring signal of the drilling process.
(3) The experimental data indicate that the signal features of the drill as it drilled in and out of the workpiece were intensified, and the correspondence between the drilling process and the vibration signal was illuminated by adopting WPMSS, which offers more accurate identification and judgment basis for drilling processing monitoring.
(4) Compared with the original spectral subtraction and wavelet transform, WPMSS can remove the signal noise more effectively, and simultaneously retain the weak features of some drilling processes.

5 ACKNOWLEDGEMENTS

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6 REFERENCES

[1] Zhou, Y. (2011). New approach to inspection of batch drilling quality based on the vibration signal mapping model. *Journal of Mechanical Engineering*, vol. 47, no. 7, p. 171, **DOI:10.3901/JME.2011.07.171**. (in Chinese)
[2] Teti, R., Jemielniak, K., O'Donnell, G., Dornfeld, D. (2010). Advanced monitoring of machining operations. *CIRP Annals*, vol. 59, no. 2, p. 717-739, **DOI:10.1016/j.cirp.2010.05.010**.
[3] Patra, K., Jha, A.K., Szalay, T., Ranjan, J., Monostori, L. (2017). Artificial neural network based tool condition monitoring in micro mechanical peck drilling using thrust force signals. *Precision Engineering*, vol. 48, p. 279-291, **DOI:10.1016/j.precisioneng.2016.12.011**.
[4] Rimpault, X., Chatelain, J.-F., Klemberg-Sapieha, J.E., Balazinski, M. (2016). Tool wear and surface quality assessment of CFRP trimming using fractal analyses of the cutting force signals. *CIRP Journal of Manufacturing Science Technology*, vol. 16, p. 72-80, **DOI:10.1016/j.cirpj.2016.06.003**.
[5] Kim, D.W., Lee, Y.S., Park, M.P., Chu, N.C. (2009). Tool life improvement by peck drilling and thrust force monitoring during deep-micro-hole drilling of steel. *International Journal of Machine Tools Manufacture*, vol. 49, no. 3-4, p. 246-255, **DOI:10.1016/j.ijmachtools.2008.11.005**.
[6] Ferreiro, S., Sierra, B., Irigoien, I., Gorritxategi, E. (2011). Data mining for quality control: Burr detection in the drilling process. *Computers & Industrial Engineering*, vol. 60, no. 4, p. 801-810, **DOI:10.1016/j.cie.2011.01.018**.
[7] Ferreiro, S., Sierra, B., Gorritxategi, E., Irigoien, I. (2010). Bayesian network for quality control in the drilling process. *IFAC Proceedings Volumes*, vol. 43, no. 4, p. 264-269, **DOI:10.3182/20100701-2-PT-4011.00046**.
[8] Peña, B., Aramendi, G., Rivero, A., López de Lacalle, L.N. (2005). Monitoring of drilling for burr detection using spindle torque. *International Journal of Machine Tools Manufacture*, vol. 45, no. 14, p. 1614-1621, **DOI:10.1016/j.ijmachtools.2005.02.006**.
[9] Ramirez, C., Poulachon, G., Rossi, F., M'Saoubi, R. (2014). Tool wear monitoring and hole surface quality during CFRP drilling. *Procedia CIRP*, vol. 13, p. 163-168, **DOI:10.1016/j.procir.2014.04.028**.
[10] Xiao, W., Zi, Y., Chen, B., Li, B., He, Z. (2014). A novel approach to machining condition monitoring of deep hole boring. *International Journal of Machine Tools Manufacture*, vol. 77, no. 2, p. 27-33, **DOI:10.1016/j.ijmachtools.2013.10.009**.
[11] Lee, S.H., Lee, D. (2008). In-process monitoring of drilling burr formation using acoustic emission and a wavelet-based artificial neural network. *International Jour-nal of Production Research*, vol. 46, no. 17, p. 4871-4888, **DOI:10.1080/00207540601152040**.
[12] D'Addona, D.M., Conte, S., Lopes, W.N., de Aguiar, P.R., Bianchi, E.C., Teti, R. (2018). Tool condition monitoring of single-point dressing operation by digital signal processing of AE and AI. *Procedia CIRP*, vol. 67, p. 307-312, **DOI:10.1016/j.procir.2017.12.218**.
[13] Hussein, R., Shaban, K.B., El-Hag, A.H. (2015). Acoustic partial discharge signal de-noising using power spectral subtraction.

IEEE Conference on Electrical Insulation and Dielectric Phenomena, p. 330-333, **DOI:10.1109/CEIDP.2015.7352003**.

[14] Kamath, S., Loizou, P. (2002). A multi-band spectral subtraction method for enhancing speech corrupted by colored noise. *IEEE International Conference on Acoustics, Speech and Signal Processing*, vol. 4, p. 4164, **DOI:10.1109/ICASSP.2002.5745591**.

[15] Paliwal, K., Wójcicki, K., Schwerin, B. (2010). Single-channel speech enhancement using spectral subtraction in the short-time modulation domain. *Speech Communication*, vol. 52, no. 5, p. 450-475, **DOI:10.1016/j.specom.2010.02.004**.

[16] Deák, K., Mankovits, T., Kocsis, I. (2016). Optimal wavelet selection for the size estimation of manufacturing defects of tapered roller bearings with vibration measurement using Shannon Entropy Criteria. *Strojniški vestnik - Journal of Mechanical Engineering*, vol. 63, no. 1, p. 3-14, **DOI:10.5545/sv-jme.2016.3989**.

[17] Plaza, E.G., López, P.J.N. (2018). Analysis of cutting force signals by wavelet packet transform for surface roughness monitoring in CNC turning. *Mechanical Systems and Signal Processing*, vol. 98, p. 634-651, **DOI:10.1016/j.ymssp.2017.05.006**.

[18] Smith, C., Akujuobi, C.M., Hamory, P., Kloesel, K. (2007). An approach to vibr-ation analysis using wavelets in an application of aircraft health monitoring. *Mechanical Systems and Signal Processing*, vol. 21, no. 3, p. 1255-1272, **DOI:10.1016/j.ymssp.2006.06.008**.

[19] Feng, Y., Schlindwein, F.S. (2009). Normalized wavelet packets quantifiers for condition monitoring. *Mechanical Systems and Signal Processing*, vol. 23, no. 3, p. 712-723, **DOI:10.1016/j.ymssp.2008.07.002**.

[20] Plaza, E.G., López, P.J.N. (2018). Application of the wavelet packet transform to vibration signals for surface roughness monitoring in CNC turning operations. *Mechanical Systems and Signal Processing*, vol. 98, p. 902-919, **DOI:10.1016/j.ymssp.2017.05.028**.

[21] Pauluzzi, D.R., Beaulieu, N.C. (2002). A comparison of SNR estimation techniques for the AWGN channel. *IEEE Transactions on Communications*, vol. 48, no. 10, p. 1681-1691, **DOI:10.1109/26.871393**.

[22] Dron, J.P., Bolaers, F., Rasolofondraibe, L. (2004). Improvement of the sensitivity of the scalar indicators (crest factor, kurtosis) using a de-noising method by spectral subtraction: Application to the detection of defects in ball bearings. *Journal of Sound and Vibration*, vol. 270, no. 1-2, p. 61-73, **DOI:10.1016/S0022-460X(03)00483-8**.

[23] Han, L., Li, C.W., Guo, S.L., Su, X.W. (2015). Feature extraction method of bearing AE signal based on improved FAST-ICA and wavelet packet energy. *Mechanical Systems and Signal Processing*, vol. 62-63, p. 91-99, **DOI:10.1016/j.ymssp.2015.03.009**.