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# On-line chatter detection and identification based on wavelet and support vector machine

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ABSTRACT

Chatter is very harmful to precision machining process. To avoid cutting chatter effectively, a method based on wavelet and support vector machine is presented for chatter identification before it has fully developed. Wavelet transform, which can image the information in both the time and frequency domain, is applied as an amplification for the chatter premonition. Each wavelet packet's energy regularly changes during the development of the chatter, which has a time advantage for the identification. Therefore, a two-dimensional feature vector is constructed for chatter detection based on the standard deviation of wavelet transform and the wavelet packet energy ratio in the chatter-emerging frequency band. A support vector machine (SVM) is designed for pattern classification based on the feature vector. The intelligent recognition system, composed of the feature extraction and the SVM, has an accuracy rate of 95% for the identification of stable, transition and chatter state after being trained by the experiment data. The method can be applied in different machining processes.



## 1. Introduction

Chatter is a kind of self-induced vibration common in the metal-cutting. In the precision machining process, the effective suppression of cutting chatter is of great significance for processing accuracy, surface finish and tool life. A variable stiffness method for chatter suppression based on magneto-rheological (MR) fluid was proposed by the authors, which was proved to be very effective through cutting experiments (Mei et al., 2009). In addition, appropriate control strategy may be designed to avoid the emergence of cutting chatter based on controllable stiffness, which relies on the on-line detection of cutting condition. Furthermore, because of some variance in cutting process, e.g. warning up of the spindle, the stable lobes diagram (SLD) may shift so that the cutting vibration system may be unstable sometime. Therefore, on-line chatter detection and identification is very necessary in order that effective method for chatter suppression can be applied in time.

For chatter detection, several sensors may be used for data acquisition, such as accelerometers (Li et al., 1997), dynamometers (Toh, 2004), microphones (Delio et al., 1992), ammeters (Soliman and Ismail, 2005) or multi-sensor approaches (Kuljanic et al., 2008). No matter which sensors are chosen, the signal processing technique is much more important, namely appropriate feature vectors should be defined for detection. In the past several years, either time series modelling (Messaoud and Weihs, 2009) or spectral analysis (Kondo et al., 1997) was used to detect chatter. Furthermore, wavelet transform (González-Brambila et al., 2006) and s-transform (Tansel et al., 2006), as time–frequency analysis methods, were also adopted for chatter detection. In addition, Cho and Eman (1988) defined feature vectors in terms of total power and dispersion of the dominant forced and chatter vibration modes extracted from linear stochastic models characterising the vibrations. Grabec et al. employ coarse-grained entropy rate as a chatter indictor in grinding (Gradiek et al., 2003) and turning (Grabec et al., 1999), whose value exhibits a drastic drop at the onset of chatter. Berger et al identified cutting states through an analysis of the singular values of a Toeqlitz matrix of third order cumulants (Berger et al., 1997) or mutual information (Berger et al., 2003). Bickraj et al. (2008) used index based reasoning (IBR) for detection of the development of chatter in end milling operations. Choi and Shin (2003) applied a wavelet-based maximum likelihood (ML) estimation algorithm to on-line chatter detection. Bao et al. (1994) detected turning chatter based on the variance of probability density function of the dynamic cutting force during stable and unstable cutting. Besides feature extraction in a chatter recognition system, a pattern classifier is required for cutting state identification. Several smart algorithms were introduced so far, such as artificial neural network (ANN) (Li et al., 1998), fuzzy logic (Bediaga et al., 2009), hidden Markov model (HMM) (Mei et al., 2007) and support vectors machine (SVM) (Jiang and Zhang, 2006). Among these algorithms, ANNs usually suffer from the problem of multiple local minima and over-fitting, while SVMs can overcome these

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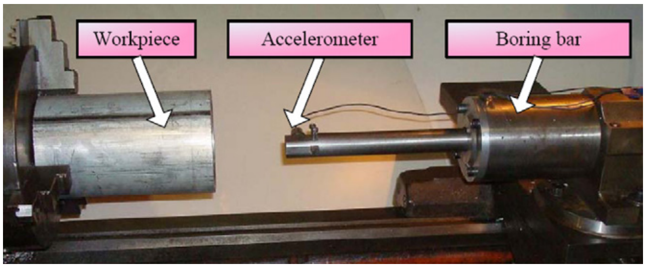


**Fig. 1.** Experimental setup for chatter detection.

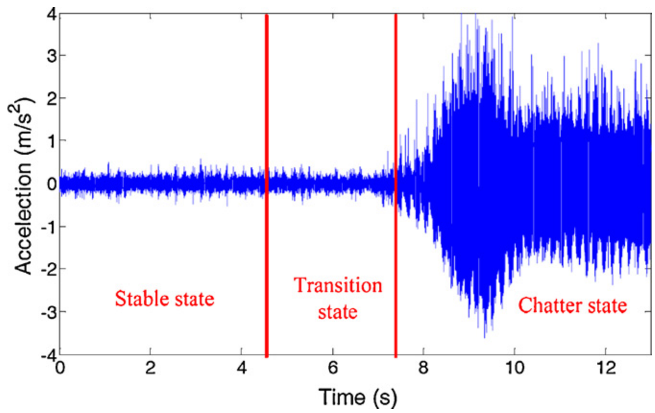


**Fig. 2.** The chatter development process in time domain.

deficiencies (Ekici, 2009). In addition, SVMs have a simple geometric interpretation and give a sparse solution. Therefore, SVMs have been widely considered as a new effective method providing efficient and powerful classification algorithms.

The chatter detection methods proposed above mostly can only detect chatter if it is already in an almost fully developed stage. It is necessary to detect the onset of chatter in such an early stage that no chatter marks are yet made on the workpiece (Faassen et al., 2006). Furthermore, appropriate chatter suppression method, such as the time-varying method based on magneto-rheological fluid proposed by Mei et al. (2009), may be applied and suppress chatter in time. However, to this day it is still a big challenge for chatter detection in this stage, which requires a fast detection algorithm including feature extraction and smart classification.

In this study, a novel method for early chatter identification in the boring process was proposed. Acceleration signal was adopted in this study for on-line detection. A two-dimensional feature vector used for chatter identification was constructed on the basis of wavelet transform. In addition, the time advantage of the feature vector was assessed. Subsequently, a support vector machine is designed for pattern classification. After supervised learning of the SVM, an excellent effect is achieved for the chatter identification.

## 2. Experimental setup for chatter detection

Experiments were conducted based on a boring bar with a diameter of 30 mm and a length diameter ratio of 6. Chatter easily emerges due to the low stiffness of the boring bar. In order to detect chatter, the horizontal vibration of the tool tip was measured by a piezoelectric accelerometer placed at the free end of the boring bar. The experimental setup is shown in Fig. 1. Accelerometer signal, which directly display the vibration, is not easy to be disturbed by environments. Based on the data acquisition of the accelerometer, chatter detection and identification can be operated. If the chatter was identified, some suppression techniques, such as the methods proposed by authors (Mei et al., 2009) can be adopted to suppress chatter in time. Usually, chatter detection and identification has two steps, they are feature extraction and feature classification.

## 3. Feature extraction based on wavelet transform

### 3.1. Features of chatter acceleration signals

Based on the experimental setup for chatter detection shown in Fig. 1, chatter acceleration signals are recorded during the machining process. Fig. 2 shows the transfer from stable cutting to chatter in the time domain. It can be seen that the amplitude increases sharply when chatter occurs. In the process of transformation from stable state to chatter state, there is a period when the vibration amplitude has not increased markedly while chatter is in its infancy clandestinely, which is called transition state. On the purpose of effective recognition of chatter, the premonition of chatter needs to be detected exactly in this period.

FFT processing results of vibration signals before and after chatter are shown in Fig. 3. It demonstrates the trend in the frequency domain in the development process of chatter, which transfers from high frequency to low frequency and from broadband to narrowband. It is shown that there are two peaks at 158.2 Hz and 345.7 Hz in the frequency spectrum of chatter signal, which are the chatter frequency and its doubling frequency, respectively.

Some features of chatter in time domain and frequency domain have been presented above. The target of early chatter identification is to detect the trend of chatter in the transition state based on some relevant features of chatter acceleration signals. Two kinds of chatter features should be considered: (1) the increase of the vibration amplitude in time domain, (2) the energy transfer in frequency domain.

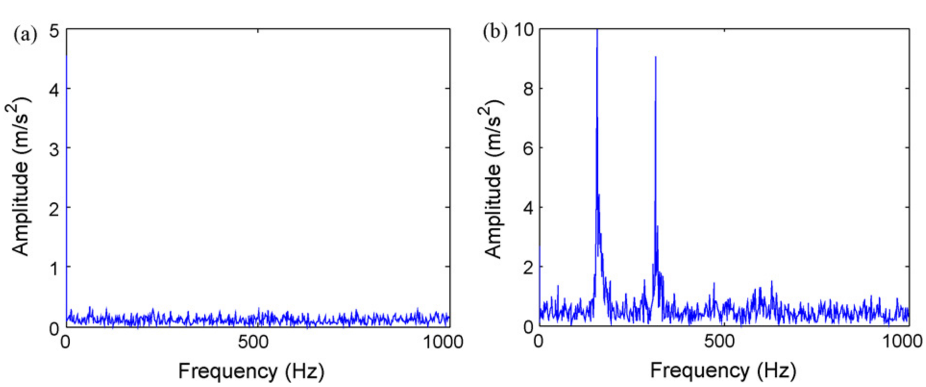


**Fig. 3.** The frequency spectrum before and after chatter: (a) stable state and (b) chatter state.

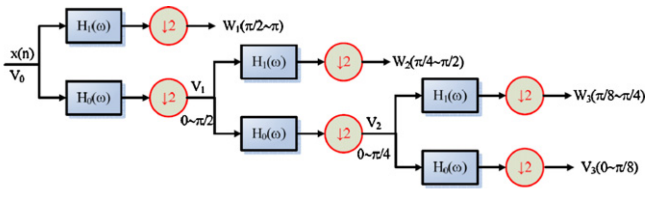


**Fig. 4.** The process of discrete wavelet transform (DWT).

### 3.2. Feature extraction based on wavelet

The random acceleration signal in stable state can be assumed to obey Gauss distribution due to statistical theory, while the one in chatter state can be described as a harmonic function with a single frequency. The process between stable state and chatter state, namely transition state, is assumed to be the complex of random signal and sine signal, which is expressed as (Bao et al., 1994)

$$a(t) = \mathrm{rand}(t) + A\ \sin\omega t, \tag{1}$$

where $t$ is the time sequence, $a(t)$ the acceleration signal, $\mathrm{rand}(t)$ the random function reflecting the signal in stable state, $\omega$ the harmonic frequency in chatter state, and $A$ is the amplitude of the chatter vibration. In addition, $A$ is an increasing variable in the transition state. For Eq. (1), if $A=0$, $a(t)=\mathrm{rand}(t)$ reflecting the signal in stable state. And if $A$ is very large, $a(t)\approx A\sin\omega t$ reflecting the signal in chatter state. Furthermore, the increasing process of $A$ corresponds to the transition from stable state to chatter state. Therefore, an effective chatter detection method is to identify chatter in the early stage when $A$ is still small.

Standard deviation in the time domain can reflect changes in the amplitude. So standard deviation of vibration acceleration signal, denoted as $\sigma(a)$, can be directly chosen as a feature parameter for chatter detection (Yeh and Lai, 1995). But when $A$ is small, standard deviation of vibration acceleration signal in the transition state does not have a remarkable change, which makes the method is restricted for application. In order to solve this problem, wavelet transform was adopted in this study. Wavelet transform is a time–frequency analysis tool, which can analyze signals simultaneously in time domain and frequency domain. Thus the results of wavelet transform usually contain a large amount of information. Based on data mining capability of wavelet transform, the chatter features might be found out in the early stage.

The process of discrete wavelet transform (DWT) (Stark, 2005) is expressed as Fig. 4. After DWT of $a(t)$, the acceleration signal is decomposed to be several signals corresponding to different frequency bands. The signal corresponding to the frequency band which chatter vibration locals in should be focused on. This signal, denoted as $\mathrm{WT}_{\mathrm{ch}}(a)$ may have remarkable characteristic for chatter as many interfering information has already been filtered. Therefore, one feature parameter $T_1$ is defined as

$$T_1 = \sigma[\mathrm{WT}_{\mathrm{ch}}(a)], \tag{2}$$

i.e., the stand deviation of the signal $\mathrm{WT}_{\mathrm{ch}}(a)$.

In order to investigate the performance of $T_1$, numerical analysis was carried out. The acceleration signal was assumed to be in stable state firstly, so the signal is simulated as a random signal with a variance of 1. After 10 s, the signal is converted into a complex signal expressed as Eq. (1). And the amplitude $A$ is assumed to be an increasing number demonstrated as $A=kt$, in which $k$ is a constant. The simulation sampling frequency was 2000 Hz. Then the simulation result of acceleration signal can be gained as shown in Fig. 5(a). Furthermore, $\sigma(a)$ and $T_1$ also can be calculated, the results are shown in Fig. 5(b).

From Fig. 5, there is no evident change in the acceleration signal $a(t)$ and $\sigma(a)$ at the beginning of transition state ($t=10$ s). Therefore,

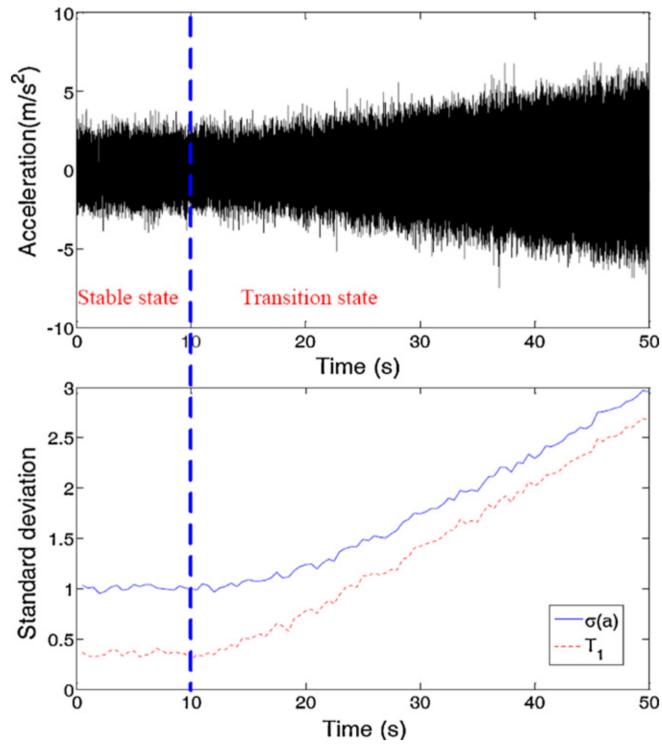


**Fig. 5.** The change of feature parameter $\sigma(a)$ and $T_1$ in chatter development process (numerical analysis).

$\sigma(a)$ is not a good feature parameter for chatter detection. However, $T_1$ has a remarkable variance at the onset of transition state, so it is much more suitable for chatter detection than $\sigma(a)$.

After numerical analysis, the advantage of $T_1$ was also investigated with experimental signals. As an example, Fig. 6 shows a section of cutting vibration acceleration signal in transition state acquired from experiments, which is figured in both the time domain and frequency domain. However, it is difficult to recognize the premonition of chatter in either domains. After 3-level decomposition and single-level reconstruction using wavelet db10 for this signal, the original signal and the decomposition level 1, 2 and 3 are shown in Fig. 7. There is an obvious exception in the decomposition level 3, in which a period of significant peaks of amplitude

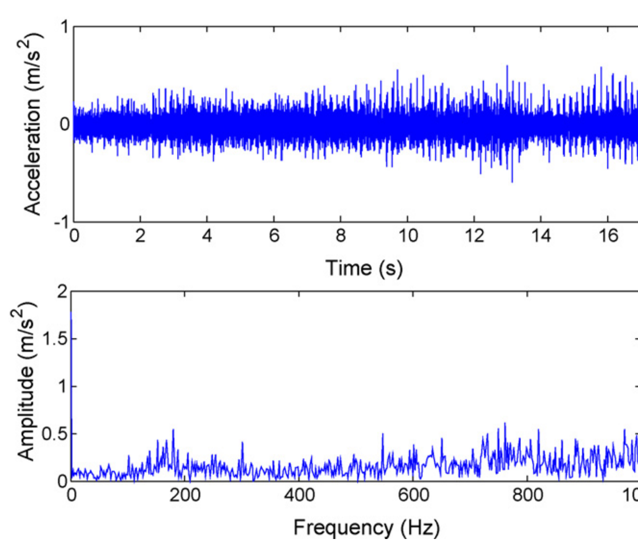


**Fig. 6.** A section of vibration acceleration signal in transition state.

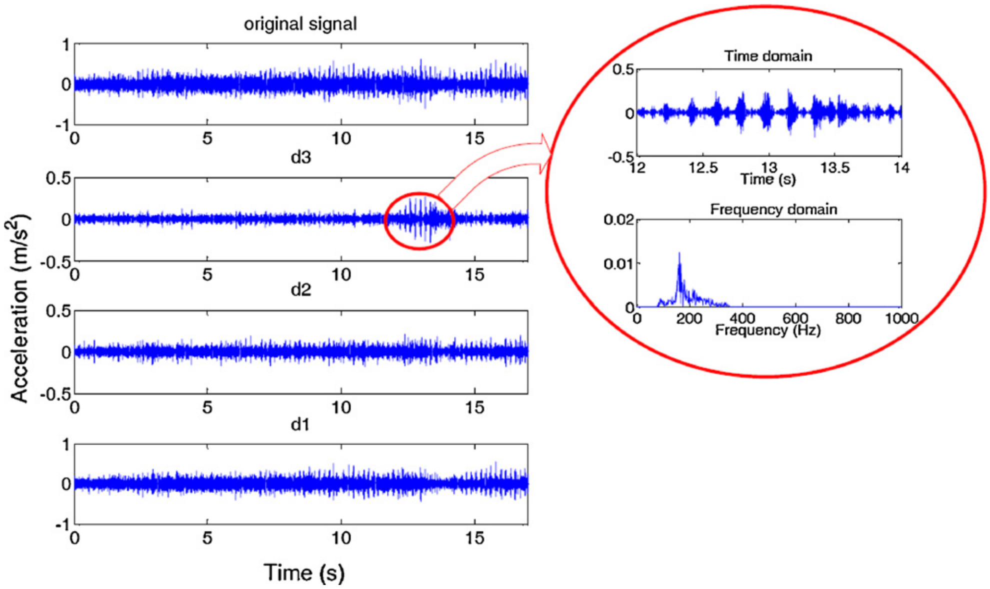


**Fig. 7.** DWT results for an acceleration signal in transition state.

emerges. The section of signal with exception in the decomposition level 3 was then taken out for further analysis. According to the sampling frequency 2000 Hz as well as the principle of DWT, it is obtained that the decomposition level 3 corresponds to 125–250 Hz frequency band. Considering the chatter frequency of 158.2 Hz mentioned in Section 3.1, the exceptional frequency band of DWT results is exactly the frequency band where chatter occurs. Based on further analysis, there is an obvious frequency peak at 164 Hz in the frequency spectrum, which is very close to the chatter frequency 158.2 Hz. Therefore, it can be considered that chatter has already been in its infancy and the energy starts to transfer to low frequency, but the energy in chatter frequency band is still in small scale, submerging in other vibration frequency components. With the help of data mining capacity of wavelet transform, the premonition of chatter can be picked out successfully.

On the basis of the above analysis, monitoring of the wavelet decomposition result in the chatter-emerging frequency band is very significant for chatter detection. In this study, the chatter-emerging frequency band is located in level 3 (125–250 Hz), which is decided by the structure parameter of the boring bar. Therefore, standard deviation of the acceleration signal in level 3 is $T_1$ mentioned before, which may be an appropriate parameter for chatter identification.

The time advantage of $T_1$ was also investigated with experimental signal. Fig. 8 shows the development process of the acceleration signal and $T_1$ based on an experimental result. It can be seen that the significant change of $T_1$ provides around 1 second's lead time for chatter suppression before the remarkable growing of vibration acceleration signal in the time domain.

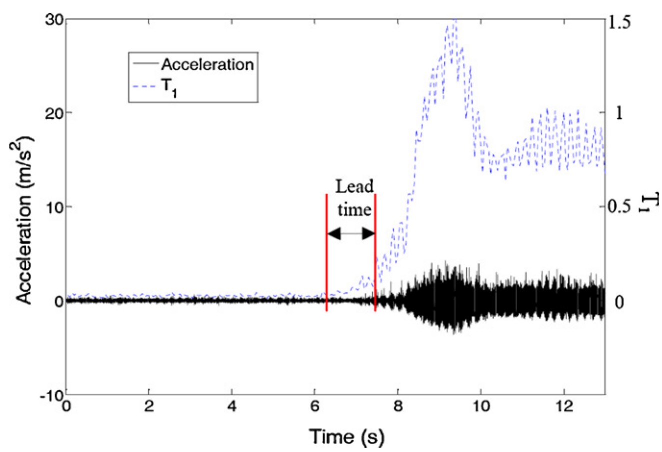


**Fig. 8.** Time advantage of $T_1$ compared to vibration acceleration signal in the time domain.

### 3.3. Feature extraction based on wavelet packet

In the process of chatter generating, the first feature is that vibration frequency begins to transfer from high frequency to low frequency, and frequency band is gradually narrowed. Then, the vibration amplitude in the time domain increases markedly. Therefore, for the detection of chatter, monitoring of the changes in the frequency domain maybe much more significant than in the time domain. As an example, Fig. 9 shows the change process of the frequency distribution when chatter emerges, which is acquired from 6-level wavelet packet decomposition. It can be seen that vibration energy increases remarkably and transfers from high frequency to

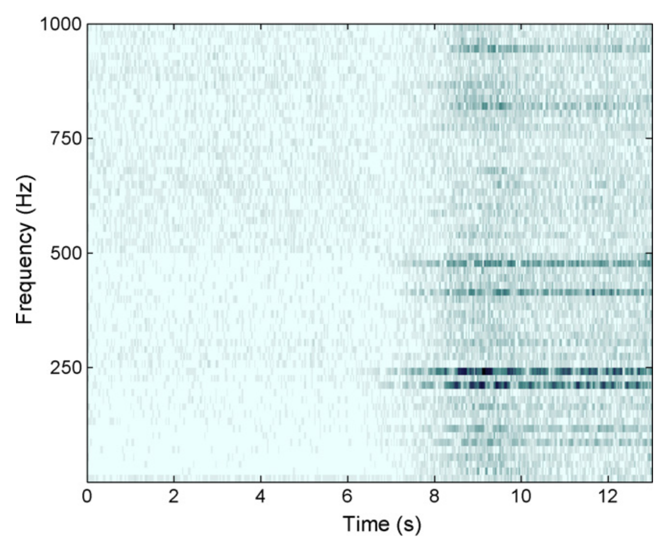


**Fig. 9.** Time–frequency analysis of a vibration acceleration signal from stable state to chatter state based on wavelet packet transform.

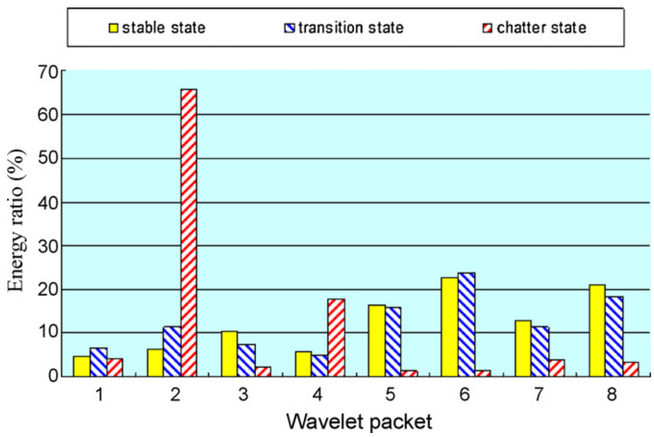


**Fig. 10.** The energy ratio of each wavelet packet in three states.

low frequency. Detecting the energy transformation in some special frequency band may be a good choice for chatter detection.

Wavelet packet transform decomposes the signal in the frequency domain as a decomposition tree and the energy of each wavelet packet can be calculated. Comparing energy of each wavelet packet clearly demonstrates the development process in frequency spectrum in the course of chatter emerging. As an example, three-level wavelet packet decomposition was applied in cutting vibration acceleration signals for stable state, transition state and chatter state, respectively. Then the energy ratios of eight wavelet packets were calculated. The results are shown in Fig. 10, in stable state before chatter emerging, the energy is concentrated in the high frequency band 500–1000 Hz. In transition state, the energy in the frequency band 125–250 Hz has been higher than other low-frequency components, but still under the energy in the high frequency. However, in chatter state, the energy in the frequency band 125–250 Hz has an absolute advantage relative to other frequency bands. Comparing the three states, it can be found that energy transfers from high frequency to low frequency and from broadband to narrowband in the process of chatter generation.

After wavelet packet transform of an acceleration signal $a(t)$, the decomposition result in chatter-emerging frequency band is denoted as $\mathrm{WPT_{ch}}(a)$. The energy percentage of $\mathrm{WPT_{ch}}(a)$ is defined as:

$$T_2 = \mathrm{Energy}[\mathrm{WPT_{ch}}(a)]. \tag{3}$$

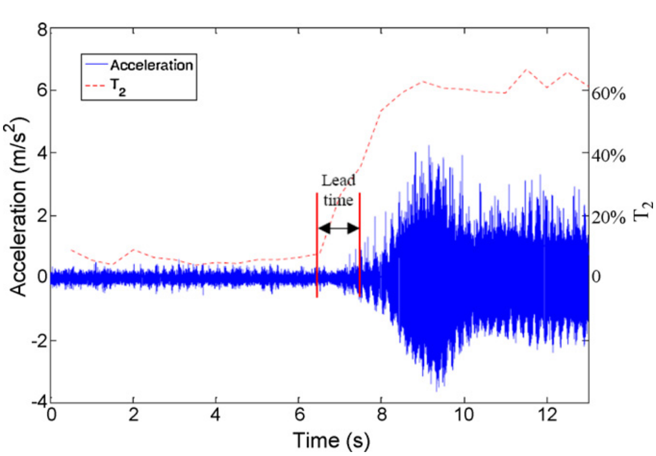


**Fig. 11.** Time advantage of $T_2$ compared to vibration acceleration signal in the time domain.

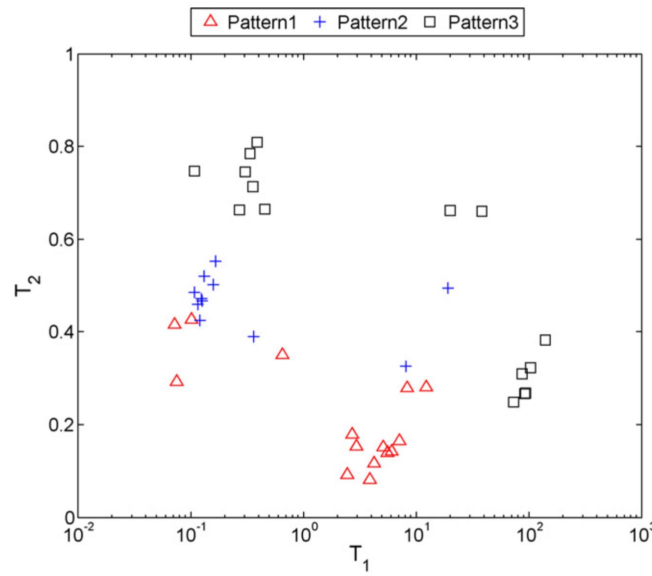


**Fig. 12.** Spatial distribution of $[T_1, T_2]$ for each pattern.

The parameter $T_2$ reflects the fundamental cause of chatter, which also has time advantage for chatter detection. The development process of $T_2$ and the vibration acceleration signal in the time domain are shown in Fig. 11. It can be found that the significant increase of $T_2$ is earlier than the increase of acceleration amplitude, which can monitor the inchoate development trend in chatter generation. Monitoring of this parameter has a time advantage of about 1 s for chatter detection.

Based on the wavelet transform and wavelet packet transform, a feature vector for chatter prediction is constructed by $[T_1, T_2]$.

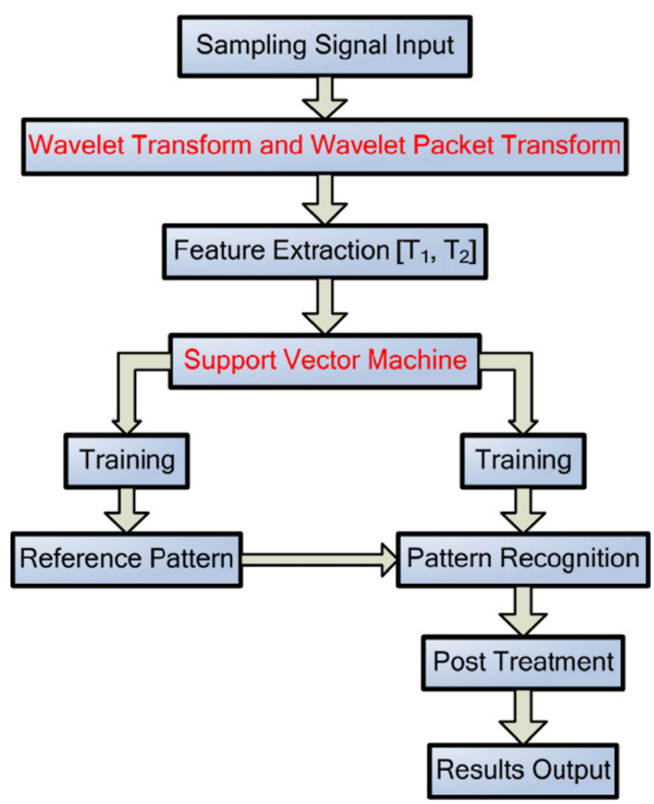


**Fig. 13.** Flow chart of the chatter recognition system.

This vector has a comprehensive response of the development in time domain, frequency domain and energy spectrum, so it is very applicable to the chatter detection and recognition.

## 4. Support vector machine for feature classification

The states in machining process can be classified into three categories: stable state (Pattern 1), transition state (Pattern 2) and chatter state (Pattern 3). Experimental data are classified according to the following rules: when the signal has a long-term and low-amplitude smooth cutting, it is considered to be in Pattern 1; when it has a prodigious amplitude or the rhythm-vibration phenomenon occurs, it is considered to be in Pattern 3; when it has a comparatively stable vibration just before remarkable chatter emerging, it is considered to be in Pattern 2.

45 section vibration signals were acquired from machining experiments under different spindle speed, cutting depth and feed rate. They were classified into three categories under the above rules, and each pattern had 15 signals. Then the feature vector [$T_1$, $T_2$] for each signal was calculated based on wavelet transform, and the spatial distribution of [$T_1$, $T_2$] of each pattern is shown in Fig. 12.

The target of pattern classification is to identify the category of signal based on the vector [$T_1$, $T_2$]. Fig. 12 shows that this classification problem can be solved by Least Square Support Vector Machine (LS-SVM). SVMs have been recognized as powerful statistical learning theory, with good performance for classification and regress, especially for small amount of training vectors (Vapnik, 1998). Despite its good performance, an original SVM might not suit for practical application, due to its time consumption during the computation of quadratic programming (Chen and Limchimchol, 2006). Thus, a least square SVM (LS-SVM) was developed by Suykens and Vandewalle (1999) for solving pattern recognition and non-linear function estimation problems. LS-SVM offers most of the properties of the original SVM, and its faster computational time is a key requirement for on-line chatter identification.

A Radial Basis Function (RBF) kernel was selected for classification. In order to distinguish the three states, a LS-SVM is required to solve a multi-class categorization problem, which is usually reformulated into a set of binary classification problems. Among the four common coding methods (one-versus-one coding, one-versus-all coding, minimum output coding, error correcting output coding), error correcting output coding is considered to be one of the best

**Table 1**
Pattern classification results of the chatter recognition system.

| No. | Input | | Output | Target | Result | Spindle speed (rpm) | Feed rate (mm/rev) | Cutting depth (mm) |
|---|---|---|---|---|---|---|---|---|
| | $T_1$ | $T_2$ | | | | | | |
| 1 | 8.3705 | 0.2789 | 1 | 1 | Correct | 320 | 0.2 | 0.5 |
| 2 | 7.139 | 0.1656 | 1 | 1 | Correct | 320 | 0.2 | 0.5 |
| 3 | 0.6583 | 0.3507 | 1 | 1 | Correct | 450 | 0.2 | 0.75 |
| 4 | 3.8705 | 0.0819 | 1 | 1 | Correct | 450 | 0.2 | 1 |
| 5 | 2.7381 | 0.179 | 1 | 1 | Correct | 900 | 0.1 | 1 |
| 6 | 0.0728 | 0.416 | 1 | 1 | Correct | 450 | 0.2 | 1 |
| 7 | 0.0757 | 0.2921 | 1 | 1 | Correct | 560 | 0.1 | 0.5 |
| 8 | 12.2681 | 0.2803 | 1 | 1 | Correct | 710 | 0.1 | 0.5 |
| 9 | 0.1028 | 0.4258 | 1 | 1 | Correct | 1120 | 0.1 | 0.75 |
| 10 | 5.1009 | 0.151 | 1 | 1 | Correct | 560 | 0.2 | 0.75 |
| 11 | 8.1702 | 0.3264 | 2 | 2 | Correct | 320 | 0.2 | 0.75 |
| 12 | 0.1665 | 0.5525 | 2 | 2 | Correct | 450 | 0.2 | 1 |
| 13 | 0.1221 | 0.4246 | 1 | 2 | Incorrect | 450 | 0.2 | 1 |
| 14 | 0.1253 | 0.4721 | 2 | 2 | Correct | 710 | 0.1 | 0.75 |
| 15 | 0.1081 | 0.4862 | 2 | 2 | Correct | 710 | 0.1 | 0.75 |
| 16 | 0.1325 | 0.5203 | 2 | 2 | Correct | 560 | 0.2 | 0.75 |
| 17 | 0.127 | 0.4672 | 2 | 2 | Correct | 710 | 0.1 | 0.75 |
| 18 | 0.1253 | 0.4721 | 2 | 2 | Correct | 710 | 0.1 | 0.5 |
| 19 | 0.1171 | 0.46 | 2 | 2 | Correct | 710 | 0.1 | 0.5 |
| 20 | 0.1081 | 0.4862 | 2 | 2 | Correct | 710 | 0.1 | 0.5 |
| 21 | 87.192 | 0.31 | 3 | 3 | Correct | 320 | 0.2 | 1 |
| 22 | 73.5797 | 0.2491 | 3 | 3 | Correct | 320 | 0.2 | 1 |
| 23 | 140.4542 | 0.3816 | 3 | 3 | Correct | 450 | 0.2 | 1 |
| 24 | 92.824 | 0.2667 | 3 | 3 | Correct | 450 | 0.2 | 1 |
| 25 | 93.1698 | 0.2681 | 3 | 3 | Correct | 560 | 0.2 | 0.75 |
| 26 | 0.3364 | 0.7854 | 3 | 3 | Correct | 560 | 0.2 | 0.75 |
| 27 | 0.2703 | 0.6639 | 3 | 3 | Correct | 450 | 0.2 | 0.75 |
| 28 | 38.185 | 0.66 | 3 | 3 | Correct | 900 | 0.1 | 0.5 |
| 29 | 0.3872 | 0.8092 | 3 | 3 | Correct | 1120 | 0.1 | 0.5 |
| 30 | 0.4564 | 0.6653 | 3 | 3 | Correct | 1120 | 0.1 | 0.5 |
| 31 | 2.4697 | 0.0917 | 1 | 1 | Correct | 320 | 0.2 | 0.75 |
| 32 | 5.5907 | 0.1398 | 1 | 1 | Correct | 450 | 0.2 | 0.5 |
| 33 | 2.9733 | 0.1533 | 1 | 1 | Correct | 450 | 0.2 | 0.5 |
| 34 | 4.2595 | 0.1164 | 1 | 1 | Correct | 1120 | 0.1 | 0.5 |
| 35 | 6.1227 | 0.1425 | 1 | 1 | Correct | 900 | 0.1 | 1 |
| 36 | 0.127 | 0.4672 | 2 | 2 | Correct | 900 | 0.1 | 0.5 |
| 37 | 0.1665 | 0.5525 | 2 | 2 | Correct | 450 | 0.2 | 1 |
| 38 | 19.3741 | 0.4946 | 2 | 2 | Correct | 560 | 0.2 | 0.5 |
| 39 | 0.159 | 0.503 | 2 | 2 | Correct | 450 | 0.2 | 0.75 |
| 40 | 0.3633 | 0.3905 | 1 | 2 | Incorrect | 450 | 0.2 | 0.5 |
| 41 | 103.4359 | 0.3232 | 3 | 3 | Correct | 450 | 0.2 | 1 |
| 42 | 0.3049 | 0.7448 | 3 | 3 | Correct | 560 | 0.2 | 0.5 |
| 43 | 0.356 | 0.7129 | 3 | 3 | Correct | 560 | 0.2 | 0.5 |
| 44 | 0.1079 | 0.7464 | 3 | 3 | Correct | 560 | 0.2 | 0.5 |
| 45 | 19.9848 | 0.6611 | 3 | 3 | Correct | 900 | 0.1 | 0.75 |

performance for the SVM with a RBF kernel (Van Gestel et al., 2002). Therefore, error correcting output coding was adopted in this study. Then, in order to classify the three patterns, a SVM was constructed using a MATLAB LS-SVM toolbox (Pelckman et al., 2002). In order to achieve a good performance, SVM parameters were optimized by *k*-fold cross-validation method, which is widely applied in SVM parameters design (Park and Lee, 2009).

## 5. Training and test of chatter recognition system

As shown in Fig. 13, a chatter recognition system is designed. It is composed of the wavelet-based feature extraction, a support vector machine and some post treatment for result output. The SVM was trained by experimental data. 10 signals of each pattern are taken out from the 45 signals on the purpose of training. And the remaining 5 signals of each pattern are used for test. The training of the SVM is performed in Matlab. The process of SVM training is actually the learning process from the expert knowledge mentioned in Section 4.

The efficiency of the recognition system after training is tested by the input of all the 30 training signals and the 15 test signals. The results are shown in Table 1. It demonstrates that most samples have been recognized correctly with an accuracy rate about 95%. It can be seen that chatter recognition system based on wavelet transform and SVM has an excellent performance for chatter premonition identification, which is robust for different cutting condition.

## 6. Conclusions and future works

In this study, an intelligent chatter recognition system based on wavelet transform and SVM was investigated via boring process. Wavelet transform has an integrated description in both time domain and frequency domain. The standard deviation of wavelet transform and the wavelet packet energy ratio in the chatter-emerging frequency band based on machining vibration acceleration signal have a fine reflection of chatter's key features. The good classification results indicate that the feature vector [$T_1$, $T_2$] is suitable to chatter premonition recognition. The design and test of the intelligent recognition system for cutting chatter identification are performed by combining the wavelet transform's feature extraction capability and the SVMs pattern classification capability. The system, through training, has an accuracy rate of about 95% for machining state recognition. When chatter transition state is monitored by the system, the chatter can be suppressed in its infancy stage by the variable stiffness chatter suppression method or some other methods.

For future work, although the feature vector based on wavelet transform mentioned above has a good performance, this vector might not be the optimal choice. How to choose and estimate the feature vector is still a challenge work for pattern recognition. Therefore, the investigation on the comparison and optimization of the feature vector is our next-step research work. The rules and methods for comparison of the feature vector will be studied. In addition, some smart algorithms for optimization of the vector will be another interesting work.

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